DROUGHT FORECASTING BY MULTI LAYER PERCEPTRON NETWORK IN DIFFERENT CLIMATOLOGY REGIONS

PREVISION DE SECHERESSE PAR LE RESEAU 'MULTI LAYER PERCEPTRON' DANS DIFFERENTES REGIONS DE CLIMATOLOGIE

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ABSTRACT

Water resources management is a complex task and is further compounded by droughts. This study applies a Multi Layer Perceptron network optimized using Levenberg-Marquardt (MLP_LM) training algorithm with a tangent sigmoid activation function to forecast quantitative values of Standard Precipitation Index (SPI) of drought at five synoptic stations in Iran. These stations belong to different climatological classes based on De Martonne aridity index. In this study, running series of total precipitation corresponding to 3, 6, 9, 12, and 24 months were used and the corresponding SPIs were calculated. The MLPs for SPIs with the one month lead time forecasting, was tested and validated. Four different input vectors were considered during network development. In the first model, MLP constructed by importing antecedent SPI with 1, 2, 3 and 4 month time lags and antecedent precipitation with 1 and 2 month time lags (MLP1). Addition of antecedent North Atlantic Oscillation (NAO) or antecedent Southern Oscillation Index (SOI) with one month time lag or both of them to MLP1 led to MLP2, MLP3 and MLP4, respectively. The MLP models were evaluated using the root mean square error (RMSE) and the coefficient of determination (R2). The results showed that MLP4 had higher prediction efficiency than did other MLPs. The more satisfactory results of RMSE and R^2 values of MLP4 for 1 month lead time for validation phase were equal to 0.35 and 0.92, respectively. Also, results indicated that MLPs can forecast SPI 24 and SPI12 more accurately than the other SPIs.

Key words: *Drought forecasting, Standard Precipitation Index, Aridity index, Artificial neural network.*

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RESUME ET CONCLUSIONS

La gestion des ressources hydriques est une tâche complexe et est encore aggravée par les sécheresses. Cette étude applique un Multi Layer Perceptron réseau optimisé à l'aide de Levenberg-Marquardt (MLP_LM) algorithme d'apprentissage avec une fonction d'activation sigmoïde tangente de prévoir des mesures quantitatives de précipitations Standard Index (SPI) de la sécheresse à cinq stations synoptiques en Iran. Ces stations appartiennent à différentes classes climatiques fondées sur l'indice d'aridité De Martonne. Dans cette étude, en cours d'exécution série de précipitations totales correspondant à 3, 6, 9, 12 et 24 mois ont été utilisés et le SPI correspondantes ont été calculées: SPI 3, SPI 6, SPI 9, SPI 12, 24 et SPI. Les MLP pour SPI avec la prévision à un mois d 'avance le temps, testé et validé. Quatre vecteurs d'entrée ont été étudiés au cours du développement du réseau. Dans le premier modèle, construit par MLP antécédent importation SPI avec 1, 2, 3 et 4 mois de temps les retards et les précipitations antérieures avec 1 et 2 mois décalages dans le temps (MLP1). Ajout d'antécédent du Nord oscillation de l'Atlantique (NAO) ou antécédent indice d'oscillation australe (SOI) avec un décalage dans le temps mois ou deux d'entre eux à MLP1 conduit à MLP2, MLP3 et MLP4, respectivement. Les modèles MLP ont été évaluées par l'erreur quadratique moyenne (RMSE) et le coefficient de détermination (R^2). Les résultats montrent que MLP4 avait une plus grande efficacité de prédiction que fait MLP autres.... Les résultats les plus satisfaisants de la RMSE et les valeurs de R2 MLP4 pour 1 fois par mois pour conduire la phase de validation ont été égal à 0,35 et 0,92, respectivement. En outre, les résultats montrent que les MLP peuvent prévisions SPI 24 et SPI12 plus de précision que peut SPI autres.

Mots clés : *Prévision de sécheresse, Index de précipitation normal, réseau index d'aridité, 'Artificial neural network'.*

(Traduction française telle que fournie par les auteurs)

1. INTRODUCTION

Drought is one of the climatic phenomena. The term meteorological drought is used to identify those situations with precipitation amounts falling short of the long-term average values. The consequential impacts of a meteorological drought may over time lead to other drought categories, i.e., agricultural, hydrological or socio/economic droughts (Dracup et al. 1980). Depending on the type of problem at hand, proper definition and application of relevant drought category must be realized. Furthermore, occurrence of drought events can have economic impacts far beyond the affected area (Mishra et al. 2007).

Drought events are usually explained by drought indicators, as variables that identify drought characteristics, i.e., the magnitude, duration, severity and spatial extent. In addition, over the years several indices have been proposed to detect and monitor droughts. As a common practice, drought indices are used to investigate occurrence and extent of drought events. One of the well known meteorological drought indices is the standardized precipitation Index (SPI), originally suggested by McKee et al. (1993).

Some of the recent researches on drought evaluation include Edossa et al. (2010), Pandey et al. (2010), Vasiliades et al. (2010) and Vangelis et al. (2010). The *SPI* has been used quite extensively, addressing a variety of drought related issues worldwide. Some of the more recent research efforts on SPI in Iran include and are not limited to; Morid et al. (2006), Jamshidi et al (2009), Modarres (2010), Abolverdi and Khalili (2010), Tabrizi et al., (2010) and Khalili et al (2010).

Mishra et al., (2007) used a hybrid model with ANN model for drought forecasting in the Kansabati River basin in India. They found the model hybrid to forecast droughts with greater accuracy. Morid et al., (2007) employed different ANN models for EDI and SPI indices to forecast drought at several rainfall stations in the Tehran Province of Iran. Jamshidi et al., (2009) applied Multi Layer Perceptron Networks optimized with three different training algorithms, including resilient back propagation, variable learning rate, and Levenberg-Marquardt, to forecast streamflow in Aspas Watershed in Fars province in southwestern Iran.

The main objective of this research is finding the capability of ANNs in forecasting of the SPI in different time series based on the data from selected stations in Iran, representing a variety of climatic zones.

2. MATERIALS AND METHODS

2.1 The SPI Drought Index

The standardized precipitation index (SPI) was developed by McKee et al. (1993), as a means to define and monitor drought events. Computation of the SPI involves fitting a probability density function (PDF) to total precipitations for the stations of interest. Typically, the gamma distribution is applied, which requires an estimation of its corresponding α, β parameters, to each time scale of interest (1, 2, 3...months) and for each month of the year. The PDF of gamma distribution is defined by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} dx$$

for $x > 0$ (1)

where α and β are shape and scale parameters, x is the precipitation amount and $\Gamma(\alpha)$ is the Gamma function. Maximum likelihood solutions are used to estimate α and β. The resulting parameters are used to find the cumulative probability of an observed precipitation event for the given month and the timescale in the given station, which is then used to obtain the SPI values. The developed SPI values are then classified into different ranges of above and below normal values, indicating the severity of drought or non-drought events. Several characteristics of droughts such as magnitude, duration or intensity can follow based on the SPI values. It is possible to have several zero values in a sample set. In order to account for zero value probability, the CDF for Gamma distribution is modified as:

$$H(x) = q + (1 - q)\, G(x) \qquad (2)$$

where, q represents the probability of zero precipitation. The calculated precipitation probabilities are transformed into the corresponding standard normal values, from which the SPI values are calculated. Additional descriptions can be found in the several available texts, i.e., Edwards and McKee (1997). A discussion of the advantages and disadvantages of using the SPI to characterize drought severity has been provided by Hayes et al. (1999). Table 1 provides a drought classification based on the SPI (McKee et al. 1993).

2.2 Neural network training algorithms

The ANN algorithms, including Levenberg-Marquardt, were first trained by minimizing the global error *E* defined as:

$$E = \frac{1}{p} \sum_{p=1}^{p} E_p \tag{3}$$

where *P* = the total number of training patterns and E_P = the error for training pattern *p*. E_P was calculated as:

$$E_p = \frac{1}{2} \sum_{k=1}^{n} (o_k - t_k)^2 \tag{4}$$

where *n* = the total number of output nodes; o_k = the network output at the *k*th output node; and t_k = the target output at the *k*th output node. In every training algorithm described in the next section an attempt was made to reduce the global error by adjusting weights and biases (Kisi, 2007).

2.3 Levenberg–Marquardt Algorithm

The Levenberg–Marquardt algorithm was designed to approach the second-order training speed without having to compute the Hessian matrix (More, 1977). When the performance function has the form of a sum of squares (as is typical in training feed forward networks), then the Hessian matrix can be approximated as:

$$H = J^T J \tag{5}$$

and the gradient can be computed as:

$$g = J^T e \tag{6}$$

where J = the Jacobian matrix that contains first derivatives of the network errors with respect to weights and biases, and e = the vector of network errors. The Jacobian matrix can be computed through a standard back-propagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{7}$$

When scalar μ is zero, this becomes just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes a gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at any iteration of the algorithm.

Table 1. The SPI drought category classification (Mckee et al. 1993)
(La classification SPI catégorie sécheresse (McKee et al. 1993))

SPI and RDI_{st} value	Category
2.0 and above	Extremely Wet
1.5 to 1.99	Very Wet
1.00 to 1.49	Moderately Wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2.0 and less	Extremely Dry

3. THE CASE STUDY AND RELEVANT DATA

Iran is located in Middle East, between Iraq and Pakistan; between 45°–63°E longitude and 25°–40°N latitude and is surrounded by Caspian Sea in North, Oman Sea and Persian Gulf in South. Occurrences of droughts are common in Iran. The total area of Iran is 1.648 million km^2. The climate classification of most of Iran is arid and semi–arid. The mean annual rainfall for Iran is less than a third of World rainfall. The long-term mean annual rainfall ranges from below 100 mm to exceeding 1000 mm. For this purpose five different synoptic stations, located in 5 provinces were selected (Figure 1). These stations are among the official sites maintained by the Iranian Meteorological Organization, and all necessary data can be accessed via http://www.weather.irsite.

The selected stations for this study mostly have 39 to 53 year records and represent a good spatial distribution over the region (Figure 1). Also, geographical location and relevant information pertaining to each station are given in Table 2. As noted in Table 2, the De Martonne aridity index (De Martonne 1942) was used to classify climatic conditions of the stations.

Fig.1. The location of the studied stations (L'emplacement des stations étudiées)

Table2. Geographical location and related information of the studied stations (Situation géographique et des informations connexes des stations étudiées)

Synoptic Station	Latitude	Longitude	Altitude (m a.s.l)	Mean Annual Rainfall (mm)	Climatic Condition
Abadan	30° 22´	48° 15´	6.6	168.6	Arid
Bandar anzali	37° 28´	49° 28´	-26.2	1779.1	Very Humid
Kermanshah	34° 17´	47° 07´	1322	462.4	Semi-Arid
Mashhad	36° 16´	59° 38´	999.2	264	Semi-Arid
Iran Shahr	27° 12´	60° 42´	591.1	111.6	Arid

4. MODELS DEVELOPMENT

Rezaeian Zadeh et al. (2010) found that the tangent sigmoid activation function is superior to the logistic sigmoid activation function in daily outflow prediction. So, for MLPs, the network structure is optimized using the Levenberg-Marquardt algorithm and tangent sigmoid activation function.

In this study, drought (SPI values) forecasting by using MLPs is considered. Four different Cases are constructed using the SPI values with time lags, precipitation data and their lag, NAO and SOI values. The following models are listed below:

$$SPI(t+1) = f(SPI(t), SPI(t-1), SPI(t-2), SPI(t-3), P(t), P(t-1)) \quad \text{(Case 1)}$$

$$SPI(t+1) = f(SPI(t), SPI(t-1), SPI(t-2), SPI(t-3), P(t), P(t-1), NAO) \quad \text{(Case 2)}$$

$$SPI(t+1) = f(SPI(t), SPI(t-1), SPI(t-2), SPI(t-3), P(t), P(t-1), SOI) \quad \text{(Case 3)}$$

$$SPI(t+1) = f(SPI(t), SPI(t-1), SPI(t-2), SPI(t-3), P(t), P(t-1), NAO, SOI) \quad \text{(Case 4)}$$

The performance of each of these input vectors is evaluated using the root mean square error (*RMSE*) and coefficient of determination (R^2). Before applying the ANN algorithm, the data is normalized to [0.05, 0.95] using the following transformation function (Soroosh et al. 2005; Rezaeian Zadeh et al. 2010):

$$X_n = 0.05 + 0.9\frac{X_r - X_{\min}}{X_{\max} - X_{\min}} \quad (8)$$

Where, X_n and X_r are the normalized input and the original input; X_{min} and X_{max} are the minimum and maximum of input data, respectively.

In order to determine the optimum input combination to the network, various epochs and neuron numbers are examined. Through this process, extracted training and testing records with various proportions are used. The architecture that produced the smallest error is used for the development of networks employed to perform drought forecasting. For Cases 1 through 4 (MLP1 to MLP4), the neuron numbers in input layer are 6, 7, 7 and 8, respectively. Furthermore, the optimum numbers of neuron in hidden layer for all models are 10. Finally, one neuron in the output layer is selected to train and test the models. The target error for the training of networks is set to 1e-4, with 50 iterations for all of 4 models. The training of the networks is stopped when their performances reached the target error. The best proportion of data was 70% for training and 30% for validation. It should be noted that tansig, tansig and purelin transfer functions are used in input, hidden and output layers, respectively. The normalized data are employed to train each of the 4 MLP models, all of which being three-layered networks.

5. RESULTS AND DISCUSSION

The evaluation of constructed models showed that the prediction results related to Case 4 (MLP4) had the lowest error (higher R^2 values and lower *RMSE* values) among the entire models. It's interesting to express that addition of NAO and SOI as input variable to the MLPs improved the prediction efficiency of the models so that in the fourth model (MLP4) the best results were obtained. So, in this study the results of MLP4 are presented (Table 3) and discussed.

Table 3. The performances of trained MLPs in validation phase (Les performances de MLP formés en phase de validation)

Station	Validation Phase (MLP4)									
	SPI3		SPI6		SPI9		SPI12		SPI24	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Abadan	0.1257	0.9038	0.2932	0.7918	0.381	0.7114	0.629	0.5253	0.6674	0.4628
Bandar Anzali	0.2524	0.8481	0.3526	0.7887	0.5079	0.6612	0.6178	0.5682	0.715	0.4136
Iran Shahr	0.242	0.8976	0.5188	0.8226	0.7639	0.6302	0.8695	0.493	0.9197	0.3969
Kermanshah	0.1947	0.9387	0.4043	0.7494	0.4398	0.6929	0.6559	0.5124	0.7079	0.3456
Mashhad	0.1368	0.912	0.2367	0.8199	0.5851	0.5757	0.7297	0.4694	0.8018	0.4265

As it is obvious from the results that the prediction efficiency of the SPI12 and also the SPI24 are higher than the other SPIs. For SPI24 and in the whole surveyed stations, the *RMSE* values are less than 0.5 and it's expressing this issue that the MLPs can predict the SPI24 superior to the other SPIs. The related values of R^2 confirm this achievement. The achieved results indicated that the MLP4 for all of the stations was applicable and it would recommend for new researches in the same climatic conditions. Evaluation of SPI12 expressed that Iran Shahr (Arid region) and Mashhad (Semi-Arid region) stations had more satisfactory results in comparison to the other stations. On the other hand, Bandar Anzali with a very humid climatic condition had the highest *RMSE* value (equal to 0.5682) and it showed that MLPs in arid and semi-arid regions had better results in the predictions but there were no noticeable differences between the results and generally, the MLPs depicted their abilities to capture the SPI variations.

For SPI24, Kermanshah and Iran Shahr stations are predicted superior to the others by using the developed MLPs. It should be noted that the *RMSE* values of Kermanshah was equal to 0.3456 and it was lower than 0.3969 (for Iran Shahr) while R^2 value of Iran Shahr was higher than the other one. In the mentioned time scale (SPI24), the prediction results related to Bandar Anzali (very humid region) is better than Abadan (arid region) station. So, there is no any dramatic improvement in the application of MLPs for drought forecasting when you are studying stations located in different climatology regions. Figures 2 and 3 display the variations of observed and predicted values related to SPI12 for the validation phase of MLP4. Based on the findings related to this study, ANNs have the strong ability to capture the variations of SPIs in different time series especially in SPI12 and SPI24.

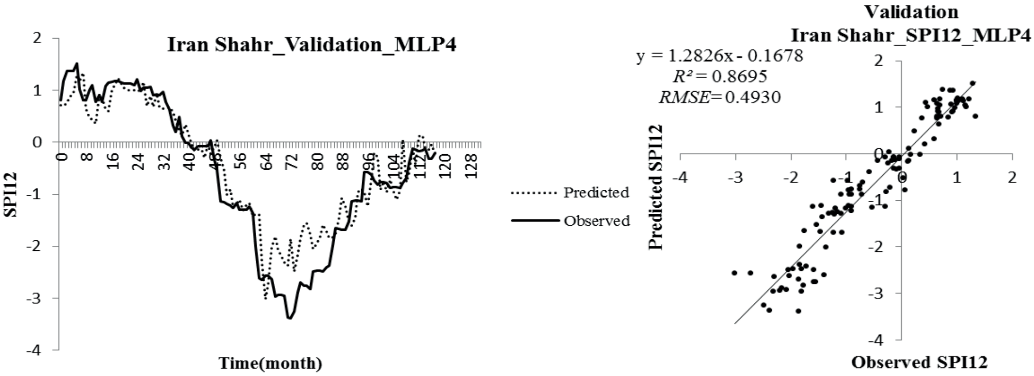

Fig. 2. The observed and predicted values of SPI12 using MLP4 in the validation phase for Iran Shahr station (Les valeurs observées et prédites de SPI12 utilisant MLP4 dans la phase de validation pour l'Iran Shahr station)

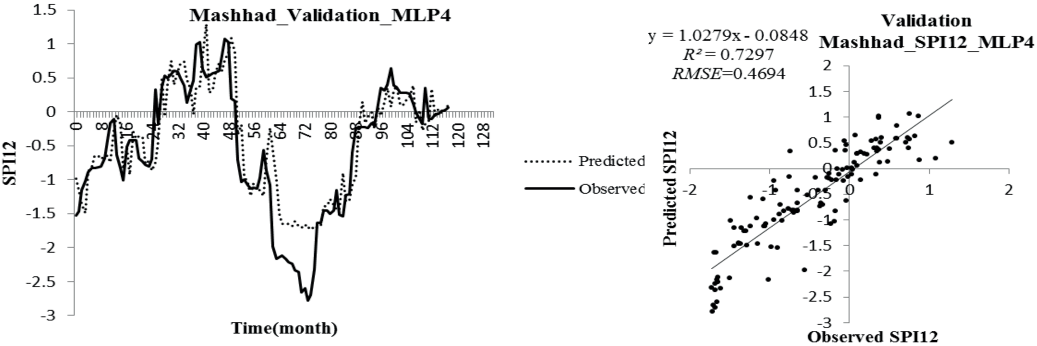

Fig. 3. The observed and predicted values of SPI12 using MLP4 in the validation phase for Mashhad station (Les valeurs observées et prédites de SPI12 utilisant MLP4 dans la phase de validation pour la station de Mashhad)

6. CONCLUSIONS AND RECOMMENDATIONS

In this study, four MLPs are applied and optimized using Levenberg-Marquardt (MLP_LM) training algorithm with a tangent sigmoid activation function to forecast quantitative values of Standard Precipitation Index (SPI) of drought at five synoptic stations in Iran located in different climatic regions. The MLPs for SPIs with the one month lead time forecasting, tested and validated. Four different input vectors were considered during network development. In the first model, MLP constructed by importing antecedent SPI with 1, 2, 3 and 4 month time lags and antecedent precipitation with 1 and 2 month time lags (MLP1). Addition of antecedent North Atlantic Oscillation (NAO) or antecedent Southern Oscillation Index (SOI) with one month time lag or both of them to MLP1 led to MLP2, MLP3 and MLP4, respectively. It's interesting to express that addition of NAO and SOI as input variable to the MLPs improved the prediction efficiency of the models so that in the fourth model (MLP4) the best results were obtained. The prediction efficiency of the SPI12 and also the SPI24 are higher than the other SPIs. For SPI24 and in the whole surveyed stations, the *RMSE* values are less than 0.5 and it's expressing this issue that the MLPs can predict the SPI24 superior to the other

SPIs. Based on the findings related to this study, ANNs have the strong ability to capture the variations of SPIs in different time series especially in SPI12 and SPI24.

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