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Prediction of Seasonal Precipitation Using Artificial Neural Networks (Case Study: Selected Stations of (Iran) Khozestan Province)

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ABSTRACT

Accurate rainfall prediction is of great interest for water management and flood control. In reality, physical processes influencing the occurrence of rainfall are highly complex, uncertain and nonlinear. In this paper, we present tool for modeling and predicting the behavioral pattern in rainfall phenomena based on past observations. The aim of this paper is to predict the seasonal rainfall of (Iran) khozestan using artificial neural network (ANN) model. In order to evaluate the prediction efficiency, we made use of 33 years of seasonal rainfall data from year 1976 to 2008 of Khozestan Province (Iran). The model were trained with 28 years of seasonal rainfall data. The ANN approache is applied to the data to derive the weights and the regression coefficients respectively. The performance of the model was evaluated by using remaining 5 years of data. The study reveals that ANN model can be used as an appropriate forecasting tool to predict the rainfall.

KEYWORDS: Neural Networks, rainfall forecast, time series.

INTRODUCTION

Accurate quantitative rainfall forecasting is one of the most desired aspects of weather prediction to the general community. Rainfall is natural climatic phenomena whose prediction is challenging and demanding. Its forecast is of particular relevance to agriculture sector, which contributes significantly to the economy of the nation. On a worldwide scale, numerous attempts have been made to predict its behavioral pattern using various techniques (Somvanishi et al., 2006). The numerical modeler is faced with the problem of predicting a physical process that could be sensitive to any of a number of factors, such as wind, temperature, and humidity, in highly nonlinear ways, including some ways that are not completely understood at the present (Rangno and Hobbs 1994). Another important factor is introduced in regions with highly variable physiography (surface features such as topography, land–water boundaries, vegetation, and soil moisture) on small scales, which can have a profound influence on any of the factors mentioned above. The general objective of this study was to simulate rainfall using artificial neural network (ANN). Artificial neural networks are mathematical models, the architecture of which has been inspired by biological neural networks (Erzin et al., 2007). ANNs are very appropriate for the modeling of nonlinear processes, such as the case of rainfall. This paper convincingly demonstrates the advantages of using ANN to model the rainfall behavior. The study of rainfall time series is a topic of great interest in the field of climatology and hydrology. Some significant examples in such areas include Singh (1998). Both univariate (e.g. Soltani et al., 2007) and multivariate (Grimaldi et al., 2005) approaches have been attempted to model the rainfall time series. Impact of other atmospheric variables on rainfall has been discussed in various literatures (Chattopadhyay, 2007b). The association between rainfall and agrometeorological processes is well discussed (e.g. Jhajharia et al., 2009; Chattopadhyay et al., 2009). Several stochastic models were attempted to forecast the occurrence of rainfall, to investigate its seasonal variability and to forecast monthly/yearly rainfall over some given geographical area. Study of the rainfall is interesting because of the associated problems, such as forecasting, corrosion effects and climate variability and various literatures have discussed these issues (Tzanis and Varotsos, 2008). Chaotic features associated with the atmospheric phenomena have attracted the attention of modern scientists (Bandyopadhyay and Chattopadhyay, 2007). Mathematical tools based on the theoretical concepts underlying the methodologies for detection and modelling of dynamical and chaotic components within a hydrological time series have been studied extensively by various scientists like Islam and Sivakumar (2002). Phase space reconstruction and artificial neural networks (ANN) are non-linear predictive tools that have been proposed in the modern literature as effective mathematical methodologies to be useful to hydrological time series characterized by chaotic features (Chattopadhyay and Chattopadhyay, 2008a; Khan et al., 2005). Applicability of ANN to rainfall time series is well documented in the literature. Prediction of atmospheric events, especially rainfall, has benefited significantly by voluminous developments in the application field of ANN and rainfall events and quantities

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have been predicted statistically (Mohanty and Mohapatra, 2007). Guhathakurata (2008) generated an ANN based model that captured the input-output non-linear relationship and predicted the monsoon rainfall in India quite accurately.

2.MATERIALS AND METHODS

2.1. Study area and rainfall data

Khuzestan Province is in south-western Iran, it covers an area of 63633/6 km^2 between latitudes 29^0 57\`- $33^0$ 4\` N and longitudes 47^0 40\`- $50^0$ 33\` E. The climate of the province is affected by weather systems from the Mediterranean and the Persian Gulf so that the weather is typically that of a semi-arid/temperate climate. Basically, the province of Khuzestan can be divided into two regions, the plains and mountainous regions. Winters in this zone are short and moderate, while the summers are long and hot. In this research, the rainfall data of stations Ahvaz , Abadan and Dezful of Khuzestan province (Iran) has been used for studying the rainfall conditions of the province, and The data for the analysis are on a seasonal basis for the period of 33 years from 1976 to 2008. In this study, the first 112 seasonal of rainfall data were used for model training. The remaining 20 seasonal of rainfall data were used for verification of the model prediction results.

2.2. Neural network model

An ANN is a massively parallel-distributed processor that has a natural propensity for storing the experimental knowledge and making it available for further use. It resembles the human brain whose speed and efficiency has been always fascinating to researchers for quite a long time. The quest to understand these processes and to solve the associated problems has led to the development of ANN technique. Neural networks essentially involve a nonlinear modeling approach that provides a fairly accurate universal approximation to any function. Its power comes from the parallel processing of the information from data. No prior assumption of the model form is required in the model building process. Instead, the network model is largely determined by the characteristics of the data. Single hidden layer feedforward network is the most widely used model form for time series modeling and forecasting. The backpropagation network (BPN) is one of the neural network algorithm which is formalized by Parker,(1986), Lippmann (1987) and Rummelhart & McClelland (1986) etc. It has been extensively used for inversion, prediction. An example of a network topology is shown in Figure 1.

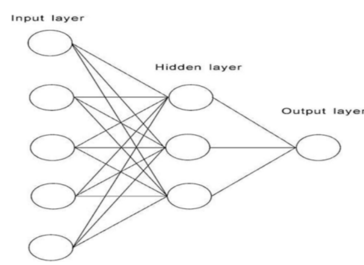

Figure 1. An example of an artificial neural network topology with one input layer, one hidden layer and one output layer

A neural network must be trained to determine the values of the weights that will produce the correct outputs. In a training step, a set of input data is used for training and presented to the network many times. The performance of the network is tested after the training step is stopped. The back propagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing most rapidly. It turns out that although the function decreases most trapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. Therefore, the basic gradient descent training algorithm is inefficient owing to its slow convergent speed and at times the poor accuracy in model predictions (Huang et al., 2004). From an optimization point of view, training a neural network can be considered as equivalent to minimizing a multivariable global error function of the network weights. There are several optimized training algorithms, as described by Haykin (1999), such as resilient back propagation, Levenberg– Marquardt and conjugated gradient back propagation. One of the optimized methods developed by Moller (1993) is the scaled conjugate gradient (SCG) algorithm. The SCG training algorithm was developed to avoid the time-consuming line search. In the conjugate gradient algorithm a search is performed along conjugate directions, which produces faster convergence than steepest descent directions. The standard backpropagation algorithm, traditionally employed in neural network learning, evaluates the gradient of the global error function with respect to the weights, f (Wk), at each iteration k, and updates the weights according to

$$W^{k+1} = W^k - \alpha^k \nabla_f (W^k) \quad (4)$$

The step size $\alpha^k > 0$ is a user-selected learning rate parameter, which affects the performance of the learning algorithm to a great extent. In all cases, the backpropagation algorithm may follow a zigzag path to the minimum, typical for a steepest gradient descent method (Falas and Stafylopatis, 2005). A conjugate gradient algorithm avoids the zigzag approach to the minimum point by incorporating a special relationship between the direction and gradient vector at each iteration. If D^k represents the direction vector at iteration k of thealgorithm, then the weight vector is updated according to the rule

$$W^{k+1} = W^k + \alpha^k D^k \quad (5)$$

Given values of W^k and D^k, a particular values of α^k that reduce the objective function as much as possible needs to be found. After a small number of iterations, the search along the line direction to find the optimum step size for the actual minimum should stop . Estimating the optimum step size with scaled conjugate gradient(SCG) training algorithm increases the learning speed and eliminates the dependence on critical user-selected parameters.The main idea behind the algorithm is the use of a factor ρ which is raised or lowered with in each iteration during the execution of the algorithm, looking at the sign of the quantity δ^k, which reveals if the Hessian matrix is not positive definite. A brief algorithm of SCG in neural network is given as follows (Falas and Stafylopatis,2005).

1.Initialization: At k=0, choose an initial weight vector W^o, and set the initial direction vector to the negative gradient vector

$D^0 = G^0 = -\nabla_f(W^0)$.

Set the scalars $0 < \delta < 10^{-4}, 0 < \rho^0 < 10^{-6}, \rho^{-0}$, set the boolean success=true.

2. If success=true, then calculate second order information:

$\sigma^k = \frac{\sigma}{|D^k|}, S_k = \frac{\left(\nabla_f(W^k+\sigma^k D^k)-\nabla_f(W^k)\right)}{\sigma^k}, \delta^k =$transpose $(D^k) + S^k$

3. Scale $\delta^k: \delta^k = \delta^k + (\rho^k - \rho^{-k})|D^k|^2$, look at the sign of δ^k for each iteration adjusting ρ^k. If $\delta^k \leq 0$ then ρ^k and Sk is estimated again.

4. If $\delta^k \leq 0$ then make the Hessian positive definite

$\rho^{-k} = 2(\rho^k - \delta^k/|D^k|^2), \quad \delta^k = -\delta^k + \rho^k|D^k|^2, \quad \rho^k = \rho^{-k}$

5. Calculate the step size: $\xi^k = transpose(D^k)G^k, \alpha^k = \frac{\xi^k}{\delta^k}$, the values of ρ^k directly scale the step size in the way, that the bigger ρ^k, the smaller the step size.

6. Calculate the comparison parameter $c^k: c^k = 2\delta^k\lfloor f(W^k) - f(W^k + \alpha^k D^k)\rfloor/(\xi^k)^2$

7. Weight and direction update:If $c^k \geq 0$, then a successful update can be made: $W^{k+1} = W^k + \alpha^k D^k, G^{k+1} = -\nabla f(W^{k+1}), \rho^{-k} = 0$, success= true. If k mod N=0 then restart algorithm with $D^{k+1} = G^{k+1} \quad else\ \beta^k = \frac{\left(|G^{k+1}|^2 - G^{k+1T}G^k\right)}{\xi^k}, D^{k+1} = G^{k+1} + \beta^k D^k. If\ c^k \geq 0.75$ then reduce the scale parameter to $\rho^k = \frac{1}{4}\rho^k\ else\ \rho^{-k} = \rho^k$, success= false.

8. If $c^k \geq 0.25$ then increase the scale parameter to $\rho^k = \rho^k + \delta^k(1 - c^k)/|D^k|^2$.

9. Repetition: If the steepest descent direction $G^k \neq 0$; set k = k+1 and go back to step 2 else terminate and return W^{k+1} as the desired minimum.

2.3. Model verification

Three different forecast consistency measures are used in order to Model verification: root mean square error (RMSE), the mean absolute percentage error (MAE) and the correlation coefficient (r).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - Q_i)^2} \quad (6)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - Q_i| \quad (7)$$

$$r = \sqrt{1 - \frac{\sum_{i=1}^{n}(P_i - Q_i)^2}{\sum_{i=1}^{n} Q_i^2 - \frac{\sum_{i=1}^{n} P_i^2}{n}}} \quad (8)$$

Here Pi and Oi are the predicted and observed values, respectively. And n is the total number of observations.

3. RESULTS AND DISCUSSION

3.1. Neural network modeling

A three-layer feed forward neural network model was developed for the prediction of seasonal rainfall using an optimized back-propagation training algorithm. In the present study, the scaled conjugated gradient algorithm was selected as the optimized training method. In the following part, artificial neural network model performances were validated for rainfall prediction under seasonally time-step condition. The data for the period between1976 and 2008 were available for the modeling purposes. seasonal rainfall time series data were divided into two independent data sets. The first data set was used for model training, and the second data set was used for model verification purposes. In the ANN modeling process, the input and output seasonal rainfall data sets for each station were normalized to the range of [0,1]. Figs. 2, 3, 4 compares the model predictions for seasonal rainfall with the observations. The verifications stage indicate that the model prediction results reasonably match the observed seasonal rainfall. The correlation coefficient between the ANN model predicted values and observed data for stations Ahvaz, Abadan and Dezful are 0.949, 0.922 and 0.945, respectively, which are satisfactory in common model applications (Figs. 5, 6, 7). These results indicate that the neural network model is able to recognize the pattern of the seasonal rainfall to provide good predictions of the seasonaly variations of seasonal rainfall data of the Khozestan Province (Iran).

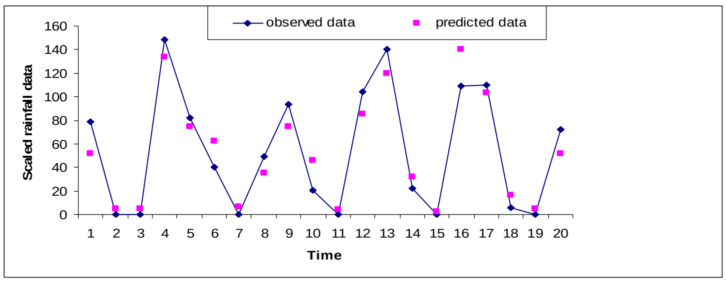

Fig. 2. ANN model verification for station Ahvaz.

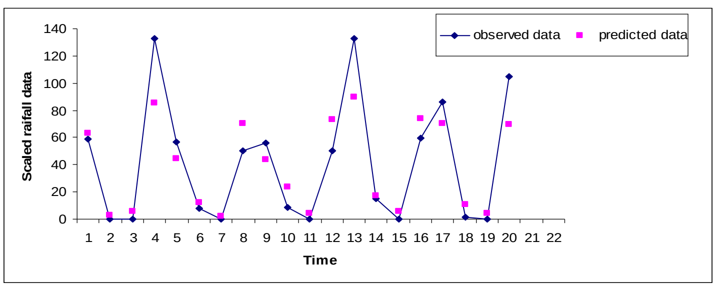

Fig. 3. ANN model verification for station Abadan.

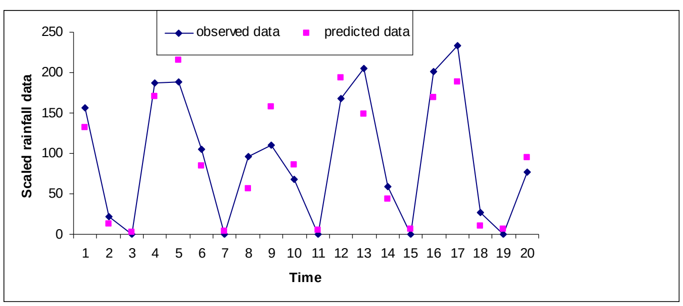

Fig. 4. ANN model verification for station Dezful.

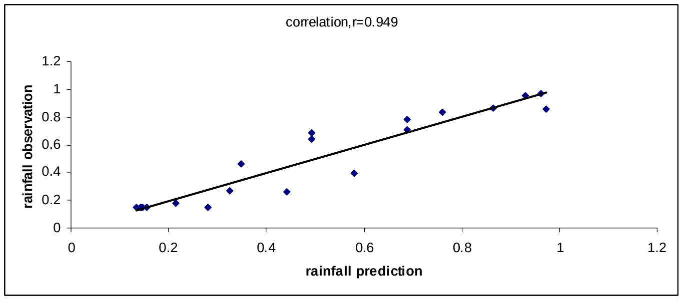

Fig. 5. Observed versus ANN predicted data for station Ahvaz.

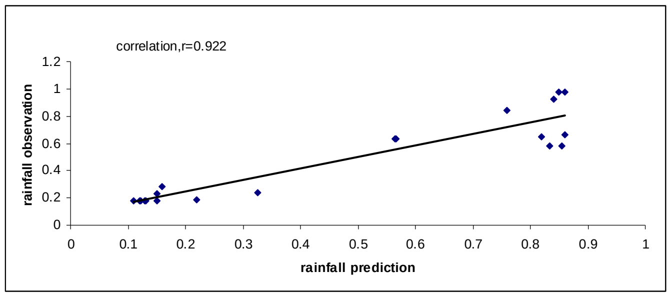

Fig. 6. Observed versus ANN predicted data for station Abadan.

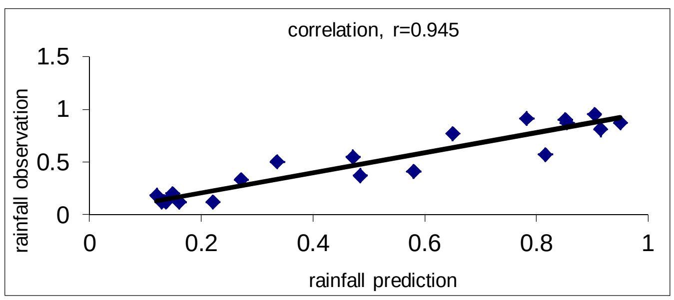

Fig. 7.

3.2. Model verification

The ANN model fits extremely well with the actual data values. the model were tested using the test data set for the period 2004 to 2008. However, the ANN approach provided reasonable precision for all stations. Tables 1, 2 ,3 gives the error estimates of the three different approach. In the case of ANN modeling approach, the RMSEs between observed and predicted data were computed as 16.13, 19.31 and 26.53 for stations Ahvaz, Abadan and Dezful, respectively. Furthermore, the MAEs between observed and predicted data for stations Ahvaz, Abadan and Dezful were appeared to be slightly lower for the ANN modeling approach. Prediction error statistics for the ANN approach produced MAEs of 37.63, 33.15 and 35.11 for stations Ahvaz, Abadan and Dezful, respectively. These results indicated that the ANN model performed well for adequate predicting of seasonal rainfall. Therefore, it can be concluded that the ANN modeling approach can give more reliable predictions of seasonal rainfall time series of Khozestan Province (Iran).

Table 1- Model verification of observed and predicted data from the ANN modeling approache for station Ahvaz.

Techniques	**Error Measures for seasonal rainfall model data set**			**Error Measures for seasonal rainfall test data set**		
ANN	RMSE	MAE	R^2	RMSE	MAE	R^2
	0.62	0.94	0.935	16.13	37.63	0.902

Table 2- Model verification of observed and predicted data from the ANN modeling approache for station Abadan.

Techniques	Error Measures for seasonal rainfall model data set			Error Measures for seasonal rainfall test data set		
ANN	RMSE	MAE	R^2	RMSE	MAE	R^2
	0.74	0.83	0.892	19.31	37.15	0.8502

Table 3- Model verification of observed and predicted data from the ANN modeling approache for station Dezful.

Techniques	Error Measures for seasonal rainfall model data set			Error Measures for seasonal rainfall test data set		
ANN	RMSE	MAE	R^2	RMSE	MAE	R^2
	0.98	0.87	0.943	26.53	35.11	0.8942

4. Conclusions

An empirical evaluation of the performance of ANN model was presented for seasonal rainfall predictions. Investigations were conducted to examine the ANN model performance for predicting rainfall in seasonally time steps. The results from the ANN model indicated that the modeling approach gave more reliable predictions of seasonal rainfall time series data. Therefore, the proposed ANN algorithm can be used for the Khozestan Province.

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