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[Research]

Artificial neural network technique for rainfall temporal distribution simulation (Case study: Kechik region)

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ABSTRACT

Artificial neural networks (ANNs) have become one of the most promising tools for rainfall simulation since a few years ago. However, most of the researchers have focused on rainfall intensity records as well as on watersheds, which generally are utilized as input records of other hydro-meteorological variables. The present study was conducted in Kechik station, Golestan Province (northern Iran). The normal multi-layer perceptron form of ANN (MLP–ANN) was selected as the baseline ANN model. The efficiency of GDX, CG and L–M training algorithms were compared to improve computed performances. The inputs of ANN included temperature, evaporation, air pressure, humidity and wind velocity in a 10 minute increment The results revealed that the L–M algorithm was more efficient than the CG and GDX algorithm, so it was used for training six ANN models for rainfall intensity forecasting. The results showed that all of the parameters were proper inputs for simulating rainfall, but temperature, evaporation and moisture were the most important factors in rainfall occurrence.

Keywords: Intensity, Rainfall, Algorithm, ANN, Kechik station

INTRODUCTION

Rainfall forecasting is vital for the planning and operation of water resources. Two basic approaches exist for this purpose, namely conceptual or physical modeling and system-theoretic or black box modeling. Conceptual models which are generally nonlinear, time-invariant, and deterministic, that involve parameters representing climatologic characteristics are used to model rainfall (Solaimani & Darvari, 2008). Rainfall forecasting plays an important role in water resource management and natural disasters management Therefore, different types of models with various degrees of complexity have been developed for this purpose. Black box models normally contain no physically-based input and output transfer functions and, therefore, are considered to be purely empirical models (Solaimani & Darvari, 2008). A series of applications have been reported since then and they range from the most recent studies (Kisi, 2004; Olsson *et al.*, 2004). Golabi *et al*. (2013) applied ANN and the ARIMA approaches to the data to derive the weights and the regression coefficients respectively. The performance of the model was evaluated by using the remaining five years of data (2008-2012). Their results showed that ANN model can be used as an appropriate simulating tool to predict the rainfall. ANNs permit diverse multi-thematic input data, but also spatial distribution of rainfall far more accurately (Richard & Gopal, 2014). Crawford and Linsley, (1966) applied digital simulation in hydrologic simulation. Bustami *et al.,* (2007) applied ANN to simulate rainfall and water level. Their results showed that ANN is an effective tool in forecasting both missing precipitation and water level data, which are indispensable to hydrologists around the globe (Hu *et al.,* 2001). Due to the ability of ANN in modeling complex nonlinear systems, successful applications of these methods in water resources modeling have been widely reported, e.g. rainfall-runoff simulation (Chang *et al.,* 2002) river flow forecasting (Imrie *et al.,* 2000; Kumar *et al.,* 2004; Mazvimavi *et al.,* 2005), rainfall forecasting (Luk *et al.,* 2001; Ramirez *et al.,* 2005) and comparison of neural infilling on missing daily weather records (Coulibaly & Evora, 2007). In the present study, the Levenberg-Marquardt and Conjugate gradient technique were employed. The Levenberg-Marquardt optimization technique is more powerful than the conventional Conjugate Gradient techniques (Cigizoglu & Kisi, 2006). As a result, wide applications in simulating very complex relationships have been found, such as wide application in modeling hydrological problems, including rainfall–runoff modeling and stream flow forecasting (Hsu *et al.,* 2002; Maier & Dandy, 2000; Riad *et al.,* 2004). The purpose of the present study was to simulate rainfall intensity using ANN capabilities.

MATERIALS AND METHODS

Site description

The present study was conducted in Kechik station, located in eastern longitude 55° 51′ 51″ and northern latitude 37° 42′ 34″ (Fig.1) of Golestan Province (northern Iran). The elevation of Kechik station is 600 m and the precipitation pattern is rainfall. The mean annual precipitation is about 490 mm. The climate of the zone is semi-humid and the total precipitation changes from 400 to 700 mm in different areas of the region. Kechik watershed contains poor range lands and dry farming terrains and a small part of the watershed is sparse forest (Gholami *et al.,* 2010). The region precipitation pattern is rain. Most rainfall occur in the autumn and winter seasons. Artificial neural network comprises a network of neurons and takes the cue from their biological counterparts, in the manner that neurons being capable of learning can be trained to find solutions, recognize patterns, classify data and even forecast future events. Such a network usually comprises many layers arranged in a series, each layer containing one or a group of neurons, and each having the same pattern of connections to the neurons in the other layer(s). A typical multi-layer feed forward neural network architecture is shown in Fig. 2. In general, the selection of input variables and output variables is problem dependent. The appropriate input variables will allow the network to successfully map the desired output and avoid the loss of important information. In the present study, the input dimensions were determined by the input variables. To determine an appropriate artificial neural network structure for simulating the rainfall in a 10 minute interval, six different models for the GDX, CG and LM algorithms were developed. Table 1 shows the summary of the different inputs. The hidden neurons from 1-20 are varied in each model and all the simulations are terminated after 1,400 iterations. Table 2 shows the comparison of different models for GDX, CG and LM algorithm, and the performance of different models is presented based on the criteria of correlation coefficient (Rsqr) and Root Mean Square Error (RMSE) Six input models planned for rainfall simulation are as follows:

$$R(t) = f\{T(t), E(t), W(t), P(t), M(t)\} \quad (1)$$

$$R(t) = f\{T(t), E(t), W(t), P(t)\} \quad (2)$$

$$R(t) = f\{T(t), E(t), W(t)\} \quad (3)$$

$$R(t) = f\{T(t), E(t)\} \quad (4)$$

$$R(t) = f\{E(t), M(t)\} \quad (5)$$

$$R(t) = f\{T(t), M(t)\} \quad (6)$$

Where; *R(t)* is rainfall value, in every 10 minute increment. *T(t)* is air temperature for every 10-minute increment. *E(t)* is evaporation for every 10 time increment. *W(t)* is Wind velocity for every 10-minute increment. *P(t)* is air pressure for every 10 time increment. *M(t)* is air moisture for every 10 minute increment. And t is scale for every 10 time increment.

The used error functions

1. Root mean squared error (RMSE)

$$\text{RMSE}=\sqrt{\sum_{i=1}^{n}\frac{(Obs-Calc)}{n}} \quad (7)$$

Obs refers to observed values, *Calc* is calculated values by network and model, and *n* is the number of data in each step. The nearer is *RMSE* to zero, the nearer are the observed and calculated values to each other and the more accurate is the simulation in each step.

2. The Pearson's R-Squared statistics (Rsqr)

$$Rsqr=\left[\frac{\sum_{i=1}^{n}(Qi-\overline{Qi}).(\hat{O}i-\tilde{O}i)}{\sqrt{\sum_{i=1}^{n}(Qi-\overline{Qi})^2.\sum_{i=1}^{n}(\hat{O}i-\tilde{O}i)^2}}\right]^2 \quad (8)$$

Where Qi is the observed value, Ôi is the estimated value and Ōi is the mean of the observed data and Õi is the mean of the estimated data and n is the number of data in each stage of test and terrain.

RESULTS

The data used in ANN were climatic data in a 10 minute increment with two years duration from 2006-7. For the mentioned models, 1000 records were used for their development; however, for the validation/testing of the model, 400 records were applied. Six model structures were developed to investigate the probability impacts of enabling/disabling temperature, evaporation, wind velocity, air pressure and air moisture as input dimensions of Kechik station. Based on the results of Root Mean Square Error (RMSE) and coefficient of determination (R) the measures were: 2.1, 0.81 (model 1); 2.4, 0.7 (model 2); 2.3, 0.78 (model 3); 2.6, 0.67 (model 4); 3.3, 0.36 (model 5); 4.1, 0.24 (model 6). Optimum network structure in rainfall simulation included a MLP with five inputs, and LM (Levenberg-Marquart) training technique and one neuron. Fig.3 shows the selection of the hidden neurons for the best structure. The results showed that the first model produces the best performance for GDX, CG and LM algorithms. After optimizing network, testing stage or efficiency evaluation is performed. Evaluation of ANN efficiency was done through comparison between estimated and actual values. From the comparison of the results in Table 2, it can be concluded that it is easy to tell the LM algorithm is superior to the GDX and CG algorithm among the used models and phases.

DISCUSSION

The results showed clearly that the artificial neural networks are capable of modeling the rainfall process. Thus, these results further confirms the general enhancement achieved by using neural networks in many other hydrological fields (Luk *et al.,* 2001; Ramirez *et al.,* 2005). Using ANN for hydrologic parameters simulation followed good results in the past and, in most cases, there have been high correlation between simulated and observed hydrographs (Chang *et al.,* 2001; Crawford & Linsley, 1996; Olsson *et al.,* 2004).

For designing dams, controlling flood and programming to manage a watershed, it is necessary to be aware of rainfall intensity values. Temperature, evaporation, wind velocity, air pressure and air moisture were selected as inputs for rainfall intensity simulation (Kisi, 2004; Kitanidis & Bras, 1980b; Legates & McCabe, 1999).

The best model structure was given in Table 2. The LM algorithm was more efficient than the CG and GDX algorithms; therefore, it was used to train the proposed six models (Fig. 3). Litta *et al.,* (2013) developed ANN model with LM algorithm to derive thunderstorm forecasts from 1 to 24 ahead at Kolkata. The final results suggested that the ANN model can be an important tool for rainfall intensity forecasting, although not replacing the forecaster s' experience, but complementing it with extra information (in addition to output model, etc.). It is true that more detailed studies are necessary due to uncertainties inherent in weather forecasting (Krzysztofowicsz, 2001). Efforts should be addressed to confront the problem of quantifying them in the ANN models (Maier & Dandy, 2000). However, in order to improve the forecasting skill of the ANN model, additional data are needed to be assimilated by the model, such as satellite images and a much longer observed rainfall intensity time-series.

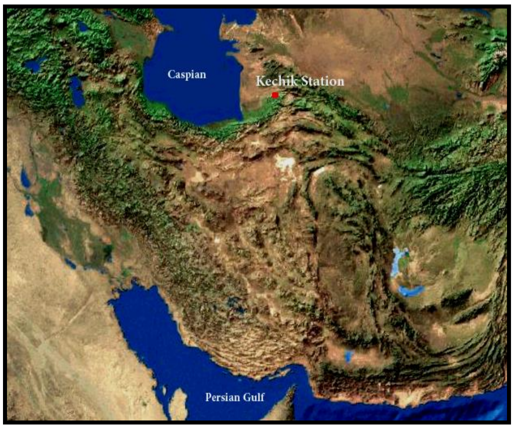

Fig. 1. Geographic location map of Kechik station

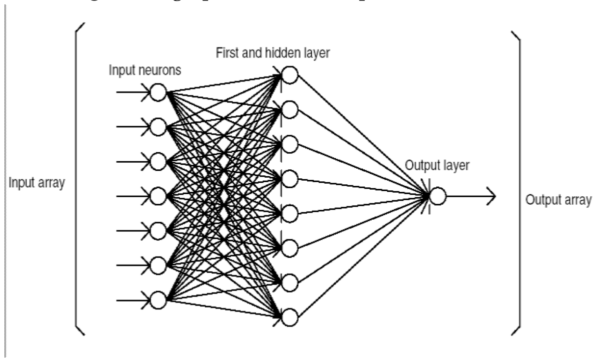

Fig. 2. A typical multi-layer feed forward neural network architecture.

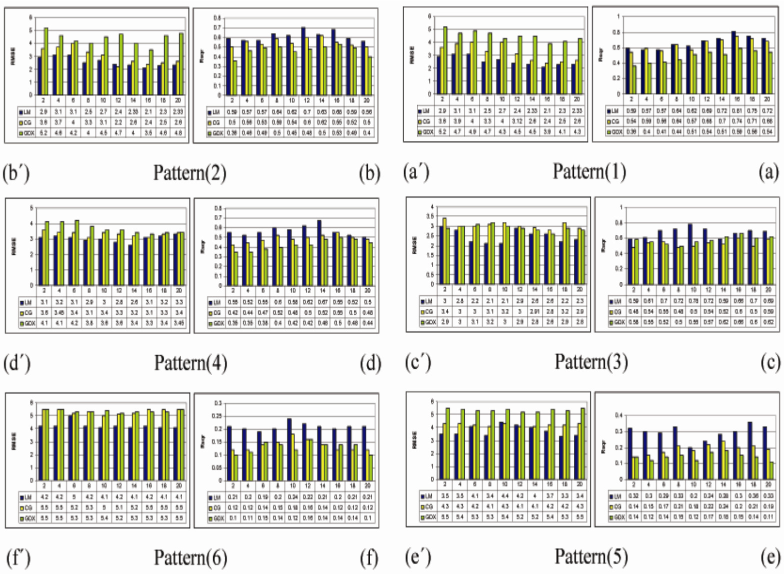

Fig 3. Comparison of convergence speeds for the (GDX), (CG) and (LM) algorithms, as measured by the number of neurons during the validation stage for Model 1 to 6; by (a,b,c,d,e,f) Correlation Coefficient (R), (a',b',c',d',e',f') Root Mean Squared Error (RMSE).

Table1. A summary of different inputs for rainfall simulation.

Time(min)	Rainfall (mm)	Temperature (c°)	Wind velocity (km/hr)	Evaporation (mm)	Pressure (mbar)	Moisture (%)
10	0	1.4	5.4	4.7	924.7	99.8
10	0.1	1.31	5.4	5.2	924.6	99.8
10	0.1	1.23	5.3	5.9	924.5	99.8
10	0	1.14	5.3	6.1	924.3	99.8
10	0	1.15	5.3	5	924.2	99.8
10	0	1.3	5.2	7.1	923.4	99.8
10	0	1.33	4.9	6.3	923.4	99.8
10	0.1	1.39	5.1	5.9	923.4	99.8
10	0	1.37	5	5	923.1	99.8
10	0	1.38	5	5.9	923.1	99.8
10	0	1.47	4.8	6.3	923.1	99.8
10	0	1.48	4.9	5.4	923.1	99.8
10	0	1.4	4.8	4.5	923	99.8
10	0	1.42	4.8	5.1	923	99.8
10	0	1.48	4.8	4.5	923.1	99.8
10	0	1.5	4.8	4.3	923	99.8
10	0	1.54	5.1	5.4	923.1	99.8
10	0	1.56	4.8	6	923.2	99.8
10	0	1.5	5.1	5.6	923.4	99.8
10	0.2	0.96	4.6	7	923.3	99.8
10	0	0.59	4.7	5.5	923.3	99.8
10	0	0.48	4.7	4.2	923.2	99.8
10	0.1	0.46	4.7	4.1	923.1	99.8
10	0	0.44	4.7	3.6	923.2	99.8
10	0.1	0.46	4.7	3	923.1	99.8
10	0.1	0.55	4.7	2.5	923.1	99.8

Table 2. Result of model performance level during training and validation stages.

model	Algorithms	Architecture	RMSE		Rsqur	
			Training	Validation	Training	Validation
	LM	5-16-1	1.8	2.1	0.92	0.81
	CG	5-16-1	2.2	2.4	0.84	0.74
model 1	GDX	5-14-1	3.3	3.9	0.64	0.59
	LM	4-18-1	2.2	2.4	0.79	0.7
	CG	4-14-1	2.4	2.6	0.71	0.62
model 2	GDX	4-16-1	3.1	3.5	0.68	0.53
	LM	3-20-1	1.9	2.1	0.82	0.78
	CG	3-16-1	2.6	2.8	0.68	0.6
model 3	GDX	3-14-1	2.4	2.6	0.74	0.66
	LM	2-14-1	2.4	2.6	0.74	0.67
	CG	2-16-1	3.1	3.3	0.62	0.55
model 4	GDX	2-16-1	3.1	3.3	0.61	0.5
	LM	2-18-1	3.2	3.3	0.44	0.36
	CG	2-14-1	3.2	4.1	0.42	0.24
model 5	GDX	2-14-1	4.1	5.2	0.26	0.18
	LM	2-20-1	4	4.1	0.3	0.24
	CG	2-16-1	4.6	5	0.28	0.18
model 6	GDX	2-14-1	4.1	5.2	0.24	0.16

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شبیه سازی توزیع زمانی بارش با استفاده از شبکه عصبی مصنوعی (ANN)

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چکیده

در طی چند دهه اخیر شبکه عصبی به عنوان ابزاری کارآمد در شبیه سازی بارش بکار گرفته شده است. محققین مطالعات متعددی برای تعیین شدت میزان بارش بر اساس پارامترهای هیدرو اقلیمی در سطح حوزه های آبخیز انجام داده اند. در تحقیق حاضر، اطلاعات ایستگاه ثبات هواشناسی کچیک در بازه های زمانی ده قیقه ای شامل دما، تبخیر، سرعت باد، فشار هوا و رطوبت بعنوان ورودی مدل و بارش بعنوان خروجی مدل مورد استفاده قرار گرفت. برای شبیه سازی توزیع زمانی بارش، شبکه پرسپترون تک لایه انتخاب گردید. بر اساس نتایج، بهترین آرایش شبکه، الگوریتم LM بدست آمد و این تائیدی بر کارایی بالای شبکه عصبی با الگوریتم LM نسبت به الگوریتم های CG و GDX در شبیه سازی توزیع زمانی بارش می باشد. همچنین، دما، تبخیر و رطوبت مهمترین ورودی ها برای شبیه سازی بارش می باشند.

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