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ORIGINAL ARTICLE

The Estimation of Evaporation Level of Pan Through Multiple Correlation Model and Neural Network Algorithm

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ABSTRACT: Artificial neural network is a new method developed to estimate and predict the parameters by using the intrinsic connections in obtained data. In this paper, the evaporation rate of pan is predicted by using Algorithm of Multilayer Perceptron Neural Network (MLP), Radial basis function Neural Network (RBFN), and Multiple Correlation Model as well as assuming linearity of pan evaporation for modeling nonlinear system of pan evaporation and using the statistics of evaporation station in the study area. The input parameters of the model are mean daily temperature, wind speed, relative mean humidity, radiation duration and height of rain, between statistical years of 2004 to 2006. The optimal number of nodes in the middle layer has been determined by trial and error method, and the performance of developed models were measured on the basis of different error parameters. The results indicate that both of the algorithms have good ability to predict the rate of evaporation from the pan. However, the radial basis function neural network algorithm estimates the evaporation rate with higher accuracy.

Keywords: evaporation of pan, neural network, multilayer perceptron, radial basis function, multiple correlation model

INTRODUCTION

Evaporation is one of the important parameters in hydrology and water resources engineering that has drawn the attention of researchers. Due to the mutual influence of various meteorological parameters in the calculation of evaporation, there are non-linear relationships to estimate the rate of evaporation with high accuracy (Dehghani, Peeri, Hesam and Dehghani, 2011). One can think about ways of reducing evaporation through accurate estimates of evaporation from open water surfaces along with analysis of sensitivity of evaporation to each one of parameters affecting it and use the considerable amount of saved waters (Mahjoubi and Tajrishi, 2012). Evaporation is a process in which the water from the soil and water sources returns back to earth atmosphere. The importance of evaporation becomes more evident annually from millions of cubic meters of fresh and salty waters of the seas; natural and artificial lakes and dams evaporate and waste. Evaporation process from lakes and reservoirs of a region cause changes in hydrological flow process in that region. This issue might cause intense changes in lakes' ecosystems and significant increase in the density of saline water of the lakes. Evaporation is necessary element of any water balance assessment done for different plans of design, utilization and management of water resources such as hydrology, agriculture, forestry, irrigation, river flow forecasting and modeling and studying of lake ecosystems. Among the components of the hydrological cycle, evaporation may be the most difficult among others because of the complicated interactions between elements of soil, plant and atmosphere in the system (Keskin, Terzi and Kucuksille, 2009).

Evaporation losses should be considered in the design of different irrigation systems and water resources. In the areas with low rainfall, these losses constitute a significant portion of the water balance assessment of lakes and reservoirs which can cause significant drop of water level (Piri, Amin, Moghaddamnia, Keshavarz, Han and Remesan, 2009). For many years, researchers and engineers have used evaporation pans to calculate the evaporation levels of lakes and water reservoirs, and measure the transpiration of plants. In this regard, the rate of evaporation from pan is measured and then by using a special coefficient, the rate of evaporation from water surface or transpiration-evaporation potential will be obtained (Dehghani et.al, 2011). Developing an alternative approach to estimate the evaporation rate on the basis of meteorological variables with ability of measuring easier estimation seems necessary. One of the recent approaches is to use the artificial neural network algorithm which is more flexible than the previous experimental models (Goel, 2009).

Sudheer, Gosain, Mohana and Saheb (2002) used the artificial neural network model for predicting evaporation from pan in an Indian area by using different meteorological variables such as the relative humidity, air temperature, wind speed and sunlight hours during a 4-year statistical period from 1990 to 1993. They found out that neural network model is more powerful than experimental model and also considering all the parameters within neural model leads to better performance (Sudheer, Gosain, Mohana and Saheb, 2002). Dehgolani et.al (2009) estimated the evaporation through ANFIS and ANN methods. They selected wind speed, saturated vapor pressure deficit and relative humidity through Gamma test as input for ANFIS and ANN. The results of their research showed the superiority of ANN to ANFIS in evaporation estimations.

Bayat Varkeshi, Zare Abayane and Maroufi (2010) believe that the estimation of evaporation from pan through ANFIS model is better than the fuzzy model. Angabini and Honarbakhsh (2011) estimated daily evaporation of pan by using artificial neural networks The results showed that the rate of evaporation from pan which through application of artificial neural networks has been calculated with the least error compared to the experimental method (Angabini, Honarbaksh, 2011). Sungwon and Hongkee (2006) studied the application of artificial neural networks, statistical regression and multi-model environment for predicting daily evaporation from pan in semi-arid region in New Delhi of India, by using daily data of six maximum and minimum air temperature, sunlight hours, wind speed and relative humidity of between 7:21-14:21 in four years from 2004 to 2007. In comparison with other methods, artificial neural network model which includes meteorological variables has the best performance in estimation of daily pan evaporation (Sudheer et.al, 2002). Piri, Amin, Moghaddamnia, Keshavarz, Han, and Remesan (2009) employed artificial neural network model to estimate evaporation rate in hot and dry regions of Chah-Nime Station of Zabol in Iran by using daily data such as air temperature, wind speed, saturation vapor pressure deficit and relative humidity in statistical period of 1995 to 2006. They showed that the neural network's performance compared with experimental models has been significant and believed that important meteorological parameters affecting the rate of evaporation are wind speed, saturation vapor pressure deficit and the relative humidity. Rahimi-khoob (2009) studied the function of artificial neural network model in predicting evaporation rate from pan by using air temperature data between 1996 and 2003 in the semi-arid region of Safi-Abad Plain of Khuzestan in south west of Iran. The results indicated acceptable performance of neural network model. Sungwon and Hongkee (2006) utilized artificial neural network to estimate evaporation of pan in rural areas of South Korea by daily data of 6 variables of maximum and minimum temperature, average temperature of dewing point, average and minimum relative moisture, average and minimum of wind speed, hours of sunlight and pan evaporation for three years in different regions. The results showed the high ability of neural networks to predict the rate of evaporation from the pan. Dehghani et.al (2011) determined the potential evaporation through fuzzy regression methods, artificial neural network and the Penman-Monteith method. The results showed the best input combination for simulation of evaporation is constituted by variables of temperature, mean relative humidity, sunshine hours and wind speed.

Materials and Methods

Data Description and Characteristics of the Region and Meteorological Stations

In this study, daily recorded data of evaporation measuring stations were used during the interval of 2004-2006. The daily inputs of meteorological parameters of the models are values of the average daily temperature, wind speed, average relative humidity, and radiation duration and rain height.

Neural network and multiple correlation models.

Considering the fact that the aim of this study is to model daily pan evaporation by using artificial neural network which consists of two multilayer perceptron algorithm, radial basis function and multiple correlation method, summarized description of artificial neural network and the structure of each method are described below

Simulation of evaporation from pan by multiple correlation equation. The evaporation is simulated based on multiple correlation method and by assuming that the evaporation from pan is independently associated with a linear combination of parameters. As a result of different scales, standardized regression was used. So the pan evaporation equation is:

$$E_t = 0.664Tmean_t + o.242Tr_t + 0.125WS_t - o.121RH_t + 0.118P_t \quad (1)$$

In the above equation, $Tmean_t$ represents mean daily temperature, Trt refers to solar radiation duration, WSt represent wind speed, RHt refers to relative humidity and P_t refers to daily rainfall.

Multilayer perceptron with neural network structure. Multilayer Neural Network, is one of the common neurological networks. This network is a part of feed-forward neural networks which are able to appropriately select a number of layers and neurons in order to do careful nonlinear mapping. Adjustable parameters in MLP network are connection weights between layers and learning process in these networks refers to finding suitable values for connection weights between neurons. A common learning algorithm networks is propagation algorithm. In this type of network, there are several hidden layers and each layer consists of one or more neurons. Neurons of one layer connect to neurons of next layer and output of one neuron in one layer just depends on neurons of previous layer to which it is connected. The most important part of determination of optimal structure of multilayer perceptron network is to determine the number of hidden layers and number of neurons in each hidden layer to achieve the least error. Figure 1 represents a simplified view of the structure of multi-layer neural network that includes input, hidden and output layers.

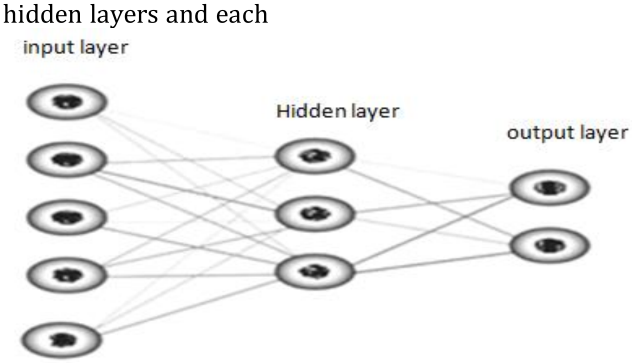

Figure 1.Structure of multi-layer perceptron neural network

There are some connections between neurons in different layers each one of which has its own weight. Through training process, these weights and constant values that are added commonly called “bias” repeatedly change in order to minimize the error between estimated values and actual values. Stimulus functions are used to transfer the output of each layer into next layers. Stimulus functions have different types the most popular of which are linear function, sigmoid function, and tangent function (Dehghani et.al, 2011).

Radial basis function neural network. The radial basis function network is of leading networks with an intermediate layer which was first introduced in 1988 by Brumahd and Lowe (Figure 2). In this method, stimulus function is often in the middle layer while Gaussian function and linear function are in the output layers. The training of RBF network is often divided into two parts the first part of which is often learning without guidance in which clustering methods are used. The parameters of base functions (center and width) are determined through using input data. In the second part which is learning with guidance, weights of middle layers and output layer are determined by using linear regression and slope reduction. In this algorithm, the space is divided via circles or mega spheres with definite center and radius. The major difference of this network with error propagation networks is that it includes one intermediate layer and neurons. stimulating functions are radial functions with specific width and center.

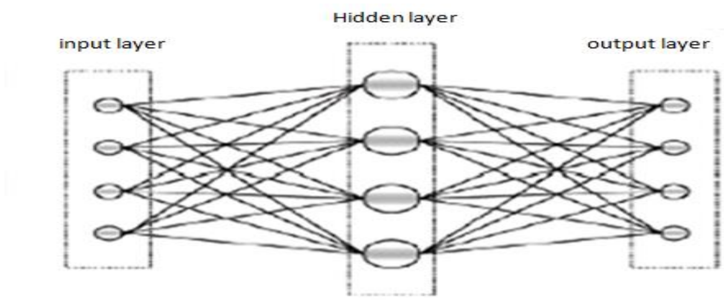

Figure 2. Structure of radial basis function of neural network structure

To increase the speed of information processing and the non-cessation of network and also because of large variations, it is better to use normalized information (0-1) as network input for some input parameter models like rainfall. Therefore in this paper, data normalization method and calculation of the value of Y are used.

$$y = (x_i-x_{min}) / (x_{max}-x_{min}) \quad (2)$$

In the above equation, Xi is the i[th] observed value, and Xmin and Xmax are respectively the minimum and maximum values of observed series. After normalization of the data, MLP and RBFN neural network were developed, and to create network, Neuro Solution-5 software was used.

Optimal structure determination of artificial neural network. To achieve the best results, various input models are defined along with the influence of their different parameters some of which are presented in Table 1. In artificial neural network, stimulus functions of sigmoid, Tangent, linear tangent and linear sigmoid are defined. In addition, for each stimulus function different training rules are used such as Levenberg Marquardt, Momentum and Conjugate Gradient. In order to reach the optimal structure, all the training rules and stimulus functions which described above were tested by trial and error. In this paper we achieved the best result by considering the sigmoid stimulus function and the Levenberg Marquardt law in all the input, intermediate and output neurons. In this regard, Adine et.al (2009) showed that consideration of stimulus functions as similar in relation to different layers of stimulus functions leads to better results. In Multilayer Perceptron Neural Network Method and in Radial basis function Neural Network Method, to find the optimal number of neurons in the middle layer trial and error method was used. In this regard, 70 percent of statistical period is recorded for training and the remaining 30% is used for the validation. In Table 2. The results of the two methods of multilayer perceptron and radial basis function are presented.

Table 1.Models Used in Simulation of Evaporation from Pan Using a Neural Network

$Et=f(Tr_t)$	model 7	$Et=f(T_t, Tr_t, RH_t, WS_t, P_t)$	Model 1
$Et=f(WS_t)$	model 8	$Et=f(T_t, Tr_t, RH_t, WS_t)$	model 2
$Et=f(P_t)$	model 9	$Et=f(Tr_t, RH_t, WS_t, P_t)$	model 3
$Et=f(T_t)$	model 10	$Et=f(T_t, Tr_t, WS_t, P_t)$	model 4
$Et=f(T_{t-1}, Tr_{t-1}, RH_{t-1}, WS_{t-1}, P_{t-1})$	model 11	$Et=f(T_t, Tr_t, RH_t, P_t)$	model 5
$Et=f(T_{t-12}, Tr_{t-12}, RH_{t-12}, WS_{t-12}, P_{t-12})$	model 12	$Et=f(RH_t)$	model 6

The values of statistical parameters used in evaluation of both neural networks and multiple correlation method are summarized in Table 3. To estimate the evaporation sensitivity rate in relation with each of the input parameters, in both methods, the models with just one parameters were developed and their performance in evaporation forecast were measured. The results of this analysis are shown in Table 4. The Comparison of the measured and predicted values of pan evaporation in the evaluation step of different methods of neural networks is shown in figures 3 and 4. In addition, a view of the multiple correlation method can be seen in Figure 5.

Table 2.Parameters Obtained from Simulation of Evaporation from Pan using Neural Networks

Model	MLP		RBFN	
Number	R2	MSE	R2	MSE
1	0.942	0.03	0.956	0.053
2	0.872	0.06	0.89	0.06
3	0.64	0.024	0.8	0.11
4	0.853	0.08	0.89	0.057
5	0.855	0.078	0.895	0.053
6	0.33	0.39	0.31	0.35
7	0.31	0.24	0.25	0.36
8	0.06	0.051	0.06	0.09
9	0.1	0.032	0.07	0.07
10	0.578	0.022	0.56	0.017
11	0.757	0.013	0.891	0.063
12	0.767	0.012	0.84	0.091

Table 3.Comparison of Accuracy of Simulation Models of Pan Evaporation

MSE	R^2	Statistical parameters
0.033	0.72	Multivariate Regression model
0.03	0.942	Multilayer Perceptron Nervation model
0.053	0.956	Radial Basis Function Nervation model

Table 4.Sensitivity Analysis of Evaporation Rate of the Different Parameters in Both Methods

Multilayer Perceptron Nervation		Radial Basis Function Nervation		input
MSE	R^2	MSE	R^2	Parameter
0.018	0.43	0.013	0.49	Taverage
0.038	0.007	0.011	0.003	Pt
0.031	0.26	0.008	0.32	RHt
0.04	0.31	0.027	0.126	Trt
0.032	0.006	0.036	0.003	WSt

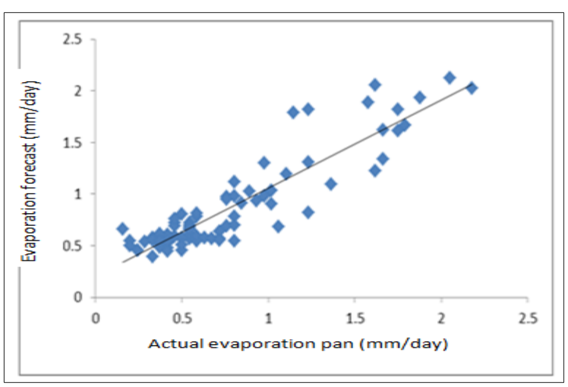

Figure 3. Comparison of measured and predicted epan in evaluation phase of a multi-layer neural network

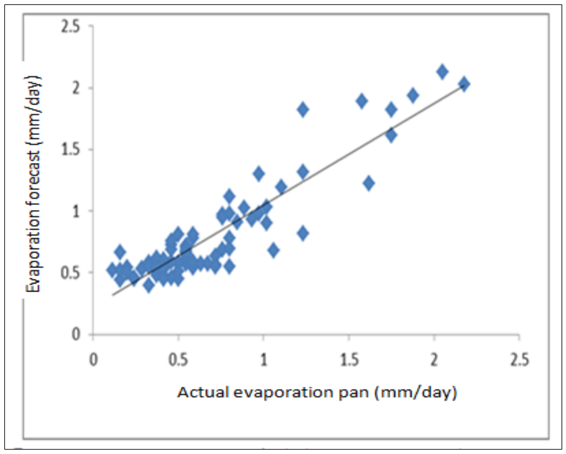

Figure 4. Comparison of measured and predicted EPan in evaluation phase for radial basis function neural network

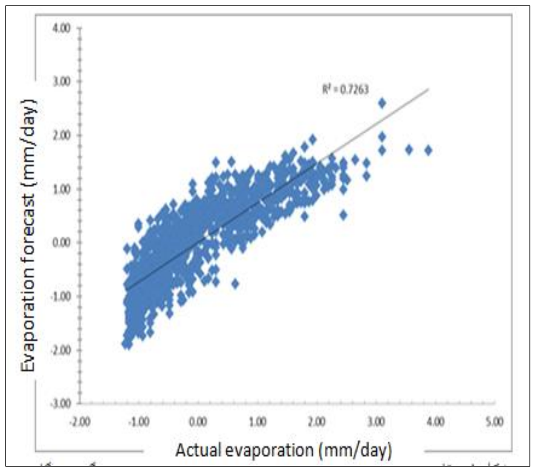

Figure 5. Comparison of actual evaporation from EPan calculated through multiple correlation equation

CONCLUSIONS

In this study, the performance of the multilayer perceptron neural network and radial basis function neural network also multiple regression method in forecasting the evaporation rate of pan were studied. By using station-based statistics of study for the interval of 2004-2006, the optimal nodes of intermediate layer in both algorithms were determined by using trial and error method. A network with 5 nodes in the input layer and 1 node in the output layer was determined as the optimal structure in both methods. The results of performance of developed models represent the proper ability of both methods compared with multiple regression method in predicting the level of evaporation of pan. The comparison of MSE values for the three methods show that radial basis function neural network has higher accuracy in predicting evaporation rate compared with multi-layered perceptron and multiple correlation method. The sensitivity analysis of the models showed that mean daily temperature, mean relative humidity, length of radiation, and height of rainfall are respectively the most influential parameters upon the value of evaporation while the influence of wind speed in this station is negligible. As shown in table 4, one can obtain an acceptable level of accuracy solely through considering the mean daily temperature. This issue is significant for regions in which the direct measurement of evaporation level is impossible.

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