Arab J Sci Eng (2012) 37:935–944
DOI 10.1007/s13369-012-0214-5

RESEARCH ARTICLE - CIVIL ENGINEERING

Seyed Saeid Eslamian · Seyed Alireza Gohari · Mohammad Javad Zareian · Alireza Firoozfar

Estimating Penman–Monteith Reference Evapotranspiration Using Artificial Neural Networks and Genetic Algorithm: A Case Study

Received: 1 October 2009 / Accepted: 7 October 2010 / Published online: 13 April 2012

Abstract The Penman–Monteith equation (PM) is widely recommended because of its detailed and comprehensive theoretical base. This method is recommended by FAO as the sole method to calculate reference evapotranspiration (ET_0) and for evaluating the other methods. The objective of this study is to compare PM using hybrid of artificial neural networks and algorithm genetic (ANN–GA) and artificial neural networks (ANNs) models for estimating ET_0 only on the basis of the meteorological data. ANNs are effective tools to model nonlinear systems and require fewer inputs, and GAs are strong tools to reach the global optimal solution. The weather stations selected for this study are located in Esfahan Province (center of Iran). The monthly meteorological data from 1951 to 2005 have been used for this study. The meteorological data were maximum, average and minimum air temperatures, relative humidity, sunshine duration and wind speed. The ANNs and ANN–GA models learned to forecast PM reference evaporation (PM ET_0). The results of this research indicate that ANN–GA predicted PM ET_0 better than ANNs model.

Keywords Reference evapotranspiration · Penman–Monteith method · Artificial neural networks · Genetics Algorithm · Esfahan

الخلاصة

إن معادلة بنمان-مونتيث (PM) يُوصى بها بشكل واسع وذلك لأن أساسها النظري مفصل و شامل. وهذه الطريقة يوصى بها من قبل منظمة FAO كطريقة وحيدة لحساب التبخر المرجعي (ET_0) ولتقييم الطرق الأخرى. إن الهدف من هذه الدراسة هو مقارنة معادلة بنمان-مونتيث باستخدام الشبكات العصبية الصناعية المزدوجة الأصلية (ANN-GA) و نماذج الشبكات العصبية الصناعية (ANNs) لحساب ET_0 فقط على أساس بيانات الأرصاد الجوية. إن نماذج الشبكات العصبية الصناعية هي أدوات فعالة لنمذجة الأنظمة غير الخطية وتحتاج مدخلات أقل، في حين أن الشبكات العصبية الصناعية المزدوجة الأصلية هي أدوات قوية للوصول إلى الحل المثالي العالمي. وتقع محطات الرصد الجوي المختارة لهذه الدراسة في مقاطعة أصفهان في وسط إيران. وتم في هذه الدراسة استخدام بيانات الأرصاد الجوية الشهرية من عام 1951 إلى عام 2005م. كانت بيانات الأرصاد الجوية هي الحدود القصوى والمعدل والحدود الدنيا لدرجات حرارة الهواء والرطوبة النسبية ومدة الشروق وسرعة الريح. إن نماذج الشبكات العصبية الصناعية المزدوجة الأصلية و نماذج الشبكات العصبية الصناعية أستفيد منها في توقعات معادلة بنمان-مونتيث للتبخر المعياري. وقد أظهرت نتائج هذا البحث أن أنموذج ANN-GA يتوقع تبخرا مرجعيا PM ET_0 بشكل أفضل من أنموذج ANNs.

S. S. Eslamian · S. A. Gohari (✉) · M. J. Zareian
Department of Water Engineering, Isfahan University of Technology,
Isfahan, Iran
E-mail: alireza_gohari@ag.iut.ac.ir

A. Firoozfar
Department of Civil and Environmental Engineering,
The University of Iowa, Iowa, USA

1 Introduction

Evapotranspiration (ET) is one of the major components of the hydrologic cycle. The estimation of evapotranspiration from a plant surface can be regarded as the basic element in the computation of the water budget and in the estimation of the water demand and supply. As more than half of the world population depends on products from irrigation agriculture, it is very important to quantify crop evapotranspiration. A common method for estimating ET from a well-watered agriculture crop is to first estimate reference crop evapotranspiration (ET_0) from a standard surface and then to apply an appropriate empirical crop coefficient (K_C), which accounts for the difference between the reference crop evapotranspiration and crop evapotranspiration. Reference evapotranspiration is measured using a lysimeter directly or can be estimated using the water budget method or the climatic variables indirectly. Because the measurements of this parameter using a lysimeter directly require much unnecessary time and needs voluble experience, it is not always possible in field measurements. Thus, an empirical approach based on the climatic variables is generally used to estimate ET_0 [1,2]. Jensen et al. [3] measured ET_0 using a lysimeter at 11 stations located in the different climatic zones of various regions around the world. They compared the results of the lysimeters with those of 20 different empirical equations and methodologies for the ET_0 measurements. It was found that Penman–Monteith (PM) method showed the optimal results over all the climatic zones. If the observed data for ET_0 does not exist, PM method can be considered as a reference methodology to estimate ET_0.

The Penman–Monteith (PM) method is recommended by FAO as appropriate to calculate ET_0 wherever the required input data are available [4,5]. The PM is a physically based approach, which requires measurements of air temperature, relative humidity, solar radiation and wind speed.

Determination of ET_0 is a complex nonlinear phenomenon because it depends on several interacting climatological factors, such as air temperature, humidity, wind speed, radiation, as well as on the type and growth stage of the crop. A tool that can be used to estimate ET_0 is the ANNs. ANNs are effective tools to model nonlinear systems and require fewer inputs. According to Sudheer et al. [6], the main advantage of ANNs methods over conventional methods is the ability for solving problems, which are difficult to formalize.

Recently, outstanding results using the ANNs model in the fields of evaporation and evapotranspiration have been obtained.

Bruton et al. [7] used weather data from Rome, Plains and Watkinsville, Georgia, consisting of 2,044 daily records from 1992 to 1996 to develop the models of daily pan evaporation. They indicated that pan evaporation estimated with ANNs models was slightly more accurate than that estimated with a multiple linear regression model or the Priestley–Taylor equation.

Trajkovic et al. [8] applied ANNs model for forecasting reference evapotranspiration (ET_0) with meteorological data of Serbia and Montenegro. The sequential adaptation of parameters and structure was achieved using an extended Kalman filter. Therefore, they suggested ANNs model for forecasting reference evapotranspiration with high reliability.

Keskin and Terzi [9] used meteorological data from Lake Eğirdir consisting of 490 daily records from 2001 to 2002 to develop the model for daily pan evaporation estimation. The results of the Penman method and ANNs models were compared to pan evaporation values. The comparison showed a better agreement between the ANNs estimations and measurements of daily pan evaporation than for other models.

Kisi [10] indicated that the generalized regression neural networks (GRNN) technique could be employed successfully in modeling the ET_0 process.

Kisi [11] investigated the modeling of ET_0 using the feed-forward artificial neural networks (ANNs) technique with the Levenberg–Marquardt (LM) training algorithm in Los Angeles, USA. It was found that the neural computing technique could be employed successfully in modeling ET_0 process from the available climatic data. The results also indicate that the Hargreaves method provides better performance than the Penman and Turc methods in the estimation of the ET_0.

Parasuraman et al. [12] compared the performance of the genetic programming models (GP) with ANNs model and the traditional Penman–Monteith (PM) method. Results indicated that both the data-driven models, GP and ANNs, performed better than the PM method. However, performance of the GP model was comparable with that of the ANNs model.

Due to its ease of application and simple architecture, the ANNs model has become a promising research field with surprising potential. Sudheer et al. [13] investigated the prediction of Class A pan evaporation (PE) using the ANNs model. They used the ANNs model for the evaporation process using proper combinations of the observed climate variables such as temperature, relative humidity, sunshine duration and wind speed for the ANNs model. Kisi [14] used the neuro-fuzzy model to estimate the daily PE using observed climatic variables.

He used proper combinations of the observed climatic variables such as air temperature, solar radiation, wind speed, pressure and relative humidity for the neuro-fuzzy model. Kumar et al. [15] developed the ANNs model to estimate the daily grass reference evapotranspiration (ET_0). They evaluated proper combinations of different climate data (solar radiation, temperature, relative humidity and wind speed) for the ANNs model. Kisi and Ozturk [16] used the neuro-fuzzy model to estimate the FAO-56 PM ET_0 using the observed climatic variables. They used proper combinations of the observed climatic variables for the neuro-fuzzy model.

In this paper, the PM, the neural network methods and GA models for estimating monthly ET_0 have been evaluated in the semiarid environment of the Esfahan Province in the center of Iran.

2 Methods and Materials

2.1 Study Area and Climate Dataset

The area under study was the Esfahan Province, which lies approximately between 32° 37′ N in latitude and between 51° 40′ E in longitude. This region is located in the center of Iran (Fig. 1).

This area is irrigated by the Zayandeh-Rood River. Esfahan Province is categorized as having a cool semi-arid climate based on the Koppen climate classification. The 54 years monthly meteorological data from 1951 to 2005 were used for this study. The meteorological data were maximum, average and minimum air temperatures, relative humidity, sunshine duration and wind speed. The data range used in the model is presented in Table 1.

The Penman–Monteith formula (Dingman [17]) is given by the following equation:

$$\mathrm{ET}_0 = \frac{0.048\Delta(R_\mathrm{n} - G) + \gamma \frac{900}{T+273} u_2 (e_\mathrm{s} - e_\mathrm{a})}{\Delta + \gamma(1 + 0.34u_2)} \tag{1}$$

where ET_0 is the reference evapotranspiration calculated by the PM method (mm day^{-1}), R_n is the daily net radiation (MJ m^2 day^{-1}), G is the soil heat flux (MJ m^2 day^{-1}), T is the average daily air temperature at 2 m

Fig. 1 Study area (Esfahan) and spatial distribution of measurement stations

Table 1 Material properties used in this investigation

	Wind speed (not)	Solar radiation (MJ m^{-2} day^{-1})	Relative humidity (%)	Temperature (°C)		
				Minimum	Average	Maximum
Data range	13.33–493.37	3.38–12.71	14–77	−9.1 to 23.9	−3 to 31.7	3.1–39.7
Data average	179.72	9.12	39.91	9.05	16.25	23.4
Data period	1951–2005	1951–2005	1951–2005	1951–2005	1951–2005	1951–2005

height (°C), U_2 is the daily mean of wind speed at 2 m height (m s^{-1}), e_s is the saturation vapor pressure (kPa), Δ is the actual vapor pressure (kPa), D is the slope of saturation vapor pressure versus air temperature curve (kPa °C^{-1}), and c is the psychometric constant (kPa °C^{-1}).

Some reliable evapotranspiration-estimating methods, like Penman–Monteith, require knowledge of the available energy expressed by the difference between net radiation (R_n) and soil heat flux (G). G is considered as either zero or portion of Rn, changing with the crop development and, thus, with the leaf area index (L). Establishment of a relationship between G/R_n and L is attempted here both for day and nighttime during the development of a crop, under varying soil moisture regimes. A reliable exponential relation between the two parameters, applicable for crops with varying geometry and architecture of canopy, is proposed for daytime. With L approaching zero, G/R_n tends to the value 0.43, whereas for large L, the ratio approaches its limit value 0.1. At night, G/R_n and L are related linearly for $L > 2$, but for smaller values of L, G approaches R_n.

All parameters were calculated using the equations provided by Allen et al. [4]. The soil heat flux, G, is the energy that is utilized in heating the soil. G is positive when the soil is warming and negative when the soil is cooling. Although the soil heat flux is small compared to R_n and may often be ignored, the amount of energy gained or lost by the soil in this process should theoretically be subtracted or added to R_n when estimating evapotranspiration.

2.2 Artificial Neural Networks

ANNs were originally designed for the modeling of the performance of a biological neural system. The internal architecture of an ANNs is similar to the structure of a biological brain with a number of layers of fully interconnected nodes or neurons. The most common architecture is composed of: the input layer, where the data are introduced into the ANNs, the hidden layer(s) where the data are processed, and the output layer where the results of given inputs are obtained (Fig. 2). This type of ANNs is called multilayer perceptron (MLP) (Fausset [18]). The other properties of ANNs model are summarized in Fig. 2. In this research, Neuro Solution 5 software was used for modeling dara [19].

Table 2 shows the specifications and optimal structure of proposed ANNs model topology.

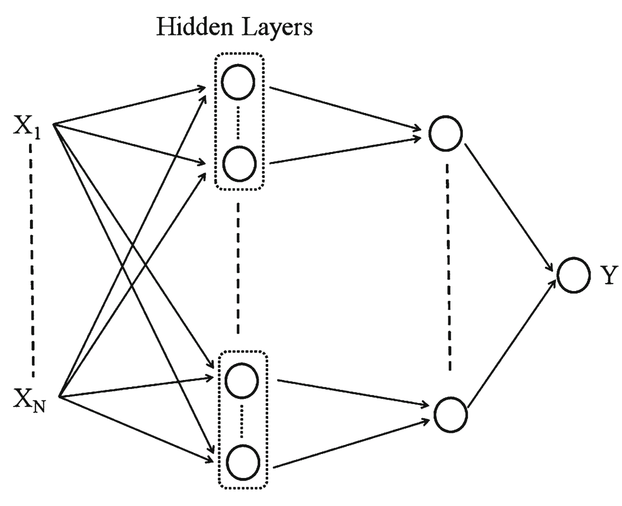

Fig. 2 Schematic of proposed ANNs model (ANNs: artificial neural networks)

Table 2 Specifications and optimal structure of proposed ANNs model topology

Learning rule	Number of neurons	Threshold function	Epoch	Momentum coefficient	Learning coefficient	Final training (repeat)	Validation error
Quick Prop	9,2	Tan H	16	0.1	0.125	10000	0.0397
Delta Rule	9,4	Tan H	1	0.4	0.5	3000	0.0705
Norm.Cum.D	6,5	Sigmoid	18	0.4	0.5	18000	0.0711
Max Prop	5,1	Tan H	9	0.8	1	17000	0.0789
Delta.Bar.De	10,3	Tan H	36	0.4	0.5	20000	0.0805
Ext DBD	5,1	Sigmoid	16	0.4	0.5	14000	0.0849

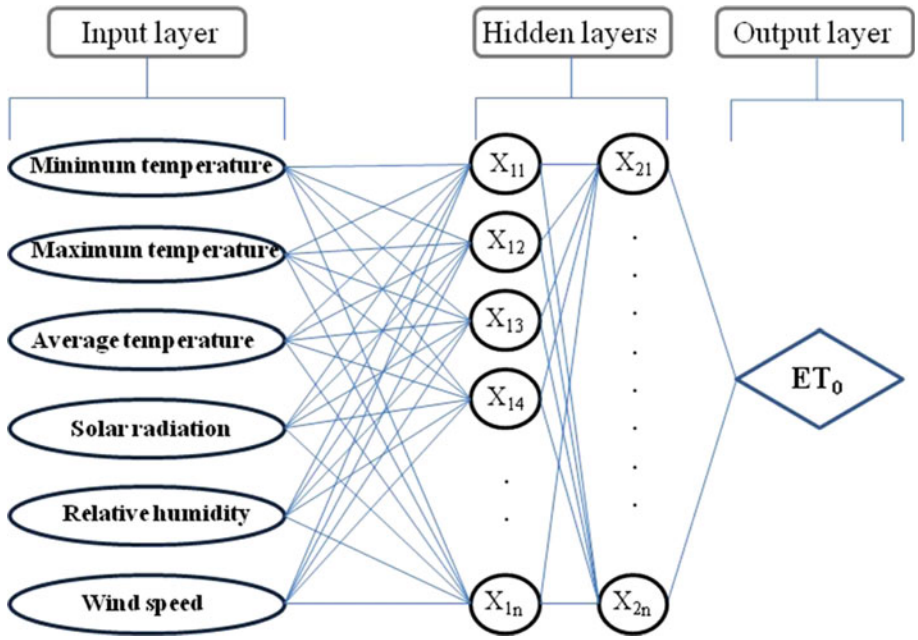

Fig. 3 Schematic of proposed GA–ANN models (GA–ANN: genetic algorithms model)

Table 3 Specifications and optimal structure of the proposed ANN–GA model topology

Learning rule	Number of neurons	Threshold function	Epoch	Momentum coefficient	Learning coefficient	Final training (repeat)	Validation error
Quick Prop	8,2	Sigmoid	12	0.4	0.25	10000	0.0438
Delta Rule	6,4	Tan H	6	0.6	0.5	5000	0.0811
Norm.Cum.D	6,4	Sigmoid	16	0.4	0.75	14000	0.0826
Max Prop	8,2	Tan H	10	0.8	1	16000	0.0851
Delta.Bar.De	9,1	Tan H	24	0.4	0.75	20000	0.0907
Ext DBD	10,1	Sigmoid	18	0.6	0.5	10000	0.0966

2.3 Genetic Algorithm

Many researchers have widely used the back propagation algorithm (BPA) for the training performance of the neural networks model. It is a first-order method based on the steepest gradient descent, with the direction vector being set equal to the negative of the gradient vector. It is also possible for the training performance to be trapped at the local minimum despite the use of a learning rate [20]. Therefore, the various methodologies have been suggested to overcome the weakness of the BPA application for the training performance of the neural networks model. The training performance of the neural networks model using the genetic algorithm (GA) starts by initializing the connection weights and the input layer nodes. The global error at the output layer of the neural networks model is then calculated as the fitness value of the objective function. These procedures are repeated from one generation to the next with the objective of reaching the global optimal solution after a sufficient number of generations. It is to be noted that a generation in the GA is highly analogous to iteration in the BPA, and the goal in both algorithms is to update the connection weights. Once the connection weights are updated at the end of a generation, the fitness value of the objective function can be calculated. In Fig. 3, input layers of GA-model consists of six meteorological parameters and output layer only consists of ET_0 [12].

Table 3 shows the specifications and optimal structure of the proposed ANN–GA model topology.

In order to compare PM methods with ANNs and hybrid method of ANNs and GA models based on temperature data, the same climatic data required for the application of the PM method were selected as input variable of the network; therefore, ANNs and hybrid method of ANNs and GA evapotranspiration models with five input variables (maximum air temperature, minimum air temperature, average air temperature, relative humidity, sunshine and wind speed) are considered. Since the purpose of this study is the estimation of ET_0, the ANNs has only one output variable. The PM estimates monthly ET_0 values that are employed as substitute for measured ET_0 data and used for output values. The number of hidden nodes in the ANNs is determined empirically by trial and error, considering the need to derive reasonable results. The inputs and outputs of the data sets were normalized to improve the performance of the network. The normalization applied was as follows:

$$xn_{i,k} = \frac{x_{i,k} - m_k}{\mathrm{SD}_k} \tag{2}$$

where $xn_{i;k}$ is the normalized input k or target data at $i = 1, 2, \ldots, N$, the index number of the data value, $x_{i,k}$ the original data, and m_k and SD_k are the mean value and standard deviation of input k or target data.

In this study, ANNs and hybrid method of ANNs, GA are employed with Neuro Solution software. 60 % of the total data were randomized for as training set for determining the weights and biases of network, 20 % of the total data were randomized for testing performance and 20 % were selected for cross-validation performance. The validation error normally decreases at the beginning of the training process. When the network starts to over-fit the data, the validation error begins to increase. The training is stopped when the validation error begins to increase, and the weights and biases will then be derived at the minimum error. The last data set is for validating the weights and biases to verify the effectiveness of the stopping criterion and to estimate the expected network operation on new data sets.

In ANNs model, multi-layer perceptron (MLP) neural networks are used that consist of two hidden layers and one output layer using log sigmoid functions. The accuracy of the networks was evaluated for each epoch in the training through mean-squared error (MSE).

For achieving a logical relation between input and output data, ANNs uses trial and error process in its training stage. But, it is obvious that this method has a great error. It might be possible that the user did not obtain an ideal relation. One of the methods which has recently been offered by researchers is the hybrid method of ANNs and GA [21,22]. Therefore, as the continuation of the program, genetic algorithm toolbox in Neuro Solution software has been used to optimize the process. The adequacy of the ANNs and GAs evapotranspiration models is evaluated by estimating the coefficient of determination (R), defined based on the evapotranspiration estimation errors as:

$$R^2 = \frac{E_0 - E}{E_0} \tag{3}$$

$$E_0 = \sum_{i=1}^{n} (\mathrm{ET}_{i\,(\text{measured})} - \mathrm{ET}_{i\,(\text{mean})})^2 \tag{4}$$

$$E = \sum_{i=1}^{n} (\mathrm{ET}_{i\,(\text{measured})} - \mathrm{ET}_{\text{simulated}})^2 \tag{5}$$

where $\mathrm{ET}_{i\,(\text{measured})}$, $\mathrm{ET}_{i\,(\text{simulated})}$ and $\mathrm{ET}_{\text{mean}}$ are monthly evapotranspiration measurement, ANNs model evapotranspiration and average of $\mathrm{ET}_{i\,(\text{measured})}$.

2.4 Mean Absolute Error (MAE) and Root Mean Square Error (RMSE)

Mean absolute error can be defined as the average value of the absolute of the difference between the calculated and observed evaporation values. A low MAE implies good model performance. A perfect match between the calculated and observed evaporation values would yield MAE = 0. This value can be calculated from the following Eq. (6).

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} \{\bar{y}_i(x) - y(x)\} \tag{6}$$

Root mean-square error is a measure of the hydrologic model. The hydrological model consists of a computer analysis of large amounts of historical data to predict how variables such as temperature, rain and carbon dioxide levels might affect outcomes. In hydrological models, various parameters must be combined so that the best relationship between input and output data is obtained. For example, in the cases that the purpose of modeling is rainfall estimate in a region, meteorological parameters should be used to model the precipitation

Table 4 The sensitivity of the reference evapotranspiration to the six meteorological variables

Sensitivity	ET_0
Maximum temperature	0.0217
Minimum temperature	0.0457
Average temperature	0.0216
Humidity	0.0495
Wind speed	0.00484
Sunshine	0.0430

Table 5 Statistical analysis of the ANNs and ANN–GA model for testing performance

Performance	ANN-GA	ANNs
MSE	0.3693	0.4669
NMSE*	0.0675	0.0813
MAE	0.4751	0.5241
Min Abs Error	0.0012	0.0096
Max Abs Error	1.6770	2.1222
R^2	0.9685	0.9036

phenomena. Although various hydrological models based on various parameters are defined, the best model is the one that has the greatest number of parameters and also where it takes place modeling has the full statistical data [22]. RMSE can be defined as the square root of the average value of the squares of the differences between the calculated and observed evaporation values. A low RMSE implies good model performance. A perfect match between the calculated and observed evaporation values would yield RMSE = 0. This value can be calculated from the following Eq. (7).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{y}_i(x) - y(x))^2} \tag{7}$$

3 Results

In this study, hybrid of artificial neural networks and algorithm genetic (ANN–GA) and artificial neural networks (ANNs) models have been used for estimating PM ET_0 only on the basis of the climatic data. The statistical parameters have been applied to compare PM methods with ANNs and hybrid method of ANNs and GA models.

3.1 Sensitivity Analysis

The sensitivity of the reference evapotranspiration to meteorological variables is shown in Table 4. It is clear that humidity, minimum air temperature and sunshine are the most sensitive variables.

Garson [20] is employed to evaluate the sensitivity of each climatic variable on PM-ET_0 with the help of the parameters of the ANNs models. While the physical process of evapotranspiration is well understood, this analysis helps explain why an ANNs model is able to accurately compute ET_0 with limited climatic data. Our results are in agreement with many researchers, who have studied the reliability of ANNs for estimating ET_0 as a function of climatic elements [6,8,23]. These researchers found satisfactory results, even better than those obtained from the PM method [15].

The testing performance applied a cross-validation method in order to overcome the overfitting of data. The cross-validation method does not train all of the training data until MSE reaches the minimum amount, but cross-validates with the testing data at the end of each performance. The correlation coefficient and MSE values are used to judge the performance of models for data. The actual and predicted values of efficiency have been also plotted. Table 5 shows the results of the statistical comparison between the hybrid of the neural network and algorithm genetic (ANN–GA) model and PM values. This table shows that for cross validation, the values of MSE, MAE and r-square (R^2) were obtained in comparison as 0.369, 0.475 and 0.968, respectively.

Table 6 The model error for different percentages of input data

Model	Test error	Validation error	Training error	Percent of training data (%)	Percent of validation data (%)
ANNs	0.0488	0.0397	0.0960	60	20
	0.1071	0.0818	0.0672	50	25
ANN-GA	0.0677	0.0434	0.109	60	20
	0.188	0.797	0.0655	50	25

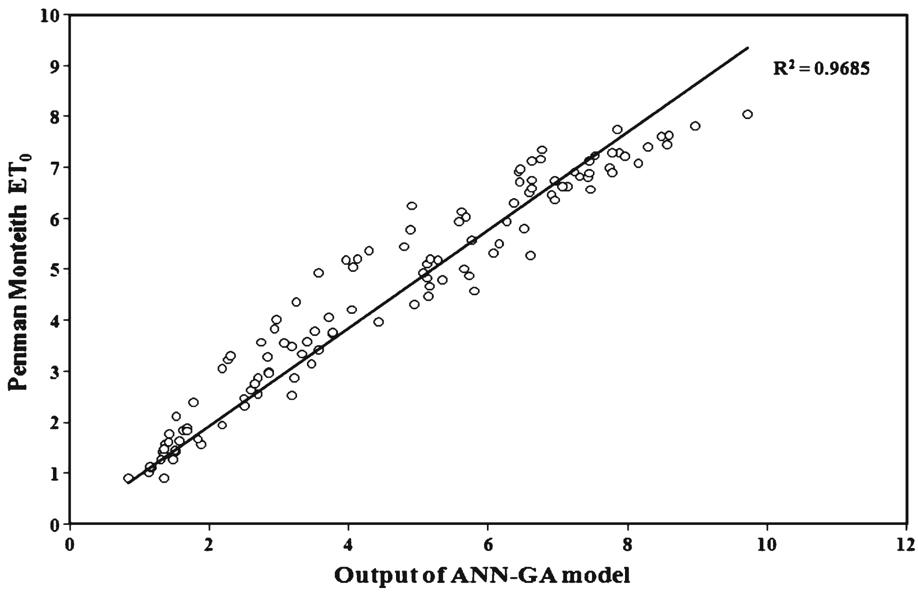

Fig. 4 Correlations between the Penman–Monteith ET_0 and output of ANN–GA model (ET_0: reference evapotranspiration; ANNs: artificial neural networks; GA: genetic algorithm)

Table 5 also shows the results of statistical comparison between the ANNs model and PM values. This table shows that for cross-validation, the values of MSE, MAE and r-square (R^2) were obtained in comparison as 0.4669, 0.5241 and 0.9035, respectively. The R^2 and MSE values were used to judge the performance of hybrid of neural network and algorithm genetic (ANN–GA) and ANNs for data set. According to the average MSE, MAE and R^2 statistics for the ANNs model (0.4669 mm day^{-1}, 0.5241 mm day^{-1} and 0.9035, respectively) and GA model (0.369 mm day^{-1}, 0.475 mm day^{-1} and 0.968, respectively), hybrid of neural network and algorithm genetic (ANN–GA) give a relatively strong agreement with PM estimates. Also, Table 6 shows the model error for different percentages of input data in ANNs and ANN–GA models.

Actual and predicted values of efficiency are also plotted. One advantage of using the hybrid of neural network and algorithm genetic (ANN–GA) is the use of a quadratic optimization, which provides a global minimum in comparison to local minima with back propagation neural network due to the use of non-linear optimization. Both hybrid neural network, genetic algorithm (ANN–GA) and ANNs are applied for determination coefficient and MSE using cross-validation and a percentage split method for the input data set comprising different attributes.

Figures 4 and 5 shows the scatter plots of ET_0 values as estimated by hybrid neural network and algorithm genetic (ANN–GA) and ANNs with PM ET_0 estimates. It can be seen that there is a close relationship between ET_0 from the PM method and the hybrid neural network and algorithm genetic (ANN–GA) method. The results suggest that the monthly ET_0 could be computed from climatic data using a hybrid of neural network and algorithm genetic. Figure 4 shows scatter plots of PM ET_0 values as estimated by the hybrid of neural network and genetic algorithm (ANN–GA). It can be found that there is a close relationship between ET_0 from the PM method and from the ANNs network. The results suggest that the monthly ET_0 could be computed from climatic data using the neural network.

Use of ANNs and GA models compared with simpler methods, such as interpolation and extrapolation methods, is more realistic. Interpolation and extrapolation methods as against ANNs and GA models are less efficient because the variation within these methods assume a linear relation in the study area. In fact, this

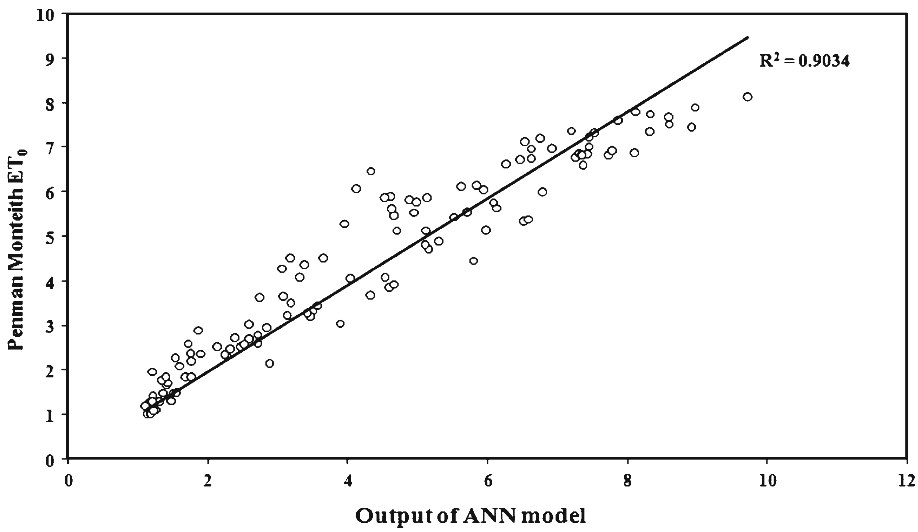

Fig. 5 Correlation between the Penman–Monteith ET_0 and output of ANNs model model (ET_0: reference evapotranspiration; ANNs: artificial neural networks)

assumption is wrong for changes in evapotranspiration, and the methods for such work are old and many researchers do not use it. Therefore, new methods like ANNs and GA may be used because linear problems of this kind of methods can be solved.

The time taken to implement the ANNs model was less than for the GA model. The reason was that the GA model had a more complex algorithm compared to the ANNs model. The run time of these models depends on the amount of data and the computer capacity that is used. So, the numbers are listed here may not apply to all cases. But, it can be said with certainty that the times of models process execution varied with various stages. These models include three stages: test, validation and training. In two models, the time of program running in validation stage is more than in other stages. In ANNs model, the time for the test stage is more than for the training stage, but in the GA model, the time for the test stage is lower than the training stage. The difference between the times of running of the models is due to difference between the ANNs and GA model algorithms.

4 Discussion

In this study, the ANNs and GA models are evaluated based on climatic data for PM ET_0 estimation. The hybrid neural network and algorithm genetic (ANN–GA) provides a quite good agreement with the evapotranspiration obtained by the Penman–Monteith method. It gives a reliable estimation at all of the locations. The overall results are of significant practical use because the climatic-based neural network can be employed when air temperature, relative humidity, radiation, and wind speed data are available.

The method that we have proposed to estimate the evapotranspiration has been used in several regions having variable climate. The rectitude of our method was found to be acceptable in all regions. The results of this study also agree well with these previous approaches. Both ANNs and GA methods have already been used by many researchers. Also, uses of these techniques are not only in hydrology and water resources, but in many other sciences. The important point is that the use of these methods by us should not be assumed as indicating a duplicate study. But, applying these methods in different areas of the world will help to enhance the credibility and accuracy of these methods and newer models that have developed algorithms, and provide material for future research.

For the recommendations for further research, we proposed that these models be used in combination with other models such as Nero-Fuzzy and SVM models. The most important factor in improving these methods is the use of these methods in all parts of the world to rectify their defects, especially in areas that have suitable meteorological data and meteorological parameters. In addition to the data used by us, the use of other meteorological parameters can help to increase the accuracy of these models.

References

1. Allen, R.G.; Jensen, M.E.; Wright, J.L.; Burman, R.D.: Operational estimates of reference evapotranspiration. Agron. J. **81**, 650–662 (1989)
2. Penman, H.L.: Natural evaporation from open water, bare soil and grass. Proc. R. Soc. Edinburgh **193**, 120–146 (1948)
3. Jensen, M.E.; Burman, R.D.; Allen, R.G.: Evapotranspiration and irrigation water requirements, ASCE Manual and Report on Engineering Practice No. 70. ASCE, NY (1990)
4. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M.: Crop evapotranspiration. Guidelines for computing crop water requirement. Irrigation and Drainage Paper No. 56 (1998)
5. Droogers, P.; Allen, R.G.: Estimating reference evapotranspiration under inaccurate data conditions. J. Irrig. Drain. Eng. ASCE **16**, 33–45 (2002)
6. Sudheer, K.P.; Gosain, A.K.; Ramasastri, K.S.: Estimating actual evapotranspiration from limited climatic data using neural computing technique. J. Irrig. Drain. Eng. ASCE **129**, 214–218 (2003)
7. Bruton, J.M.; McClendon, R.W.; Hoogenboom, G.: Estimating daily pan evaporation with artificial neural networks. Trans. ASAE **43**, 491–496 (2000)
8. Trajkovic, S.; Todorovic, B.; Stankovic, M.: Forecasting reference evapotranspiration by artificial neural networks. J. Irrig. Drain. Eng. ASCE **129**, 454–457 (2003)
9. Keskin, M.E.; Terzi, O.: Artificial neural networks models of daily pan evaporation. J. Hydrol. Eng. ASCE **11**, 65–70 (2006)
10. Kisi, O.: Generalized regression neural networks for evapotranspiration modeling. Hydrol. Sci. J. **51**, 1092–1105 (2006)
11. Kisi, O.: Evapotranspiration modeling from climatic data using a neural computing technique. Hydrol. Process. **21**, 1925–1934 (2007)
12. Parasuraman, K.; Elshorbagy, A.; Carey, S.K.: Modeling the dynamics of the evapotranspiration using genetic programming. Hydrol. Sci. J. **52**, 563–578 (2004)
13. Sudheer, K.P.; Gosain, A.K.; Rangan, D.M.; Saheb, S.M.: Modeling evaporation using an artificial neural network algorithm. Hydrol. Process. **16**, 3189–3202 (2002)
14. Kisi, O.: Daily pan evaporation modeling using a neuro-fuzzy computing technique. J. Hydrol. **329**, 636–646 (2006)
15. Kumar, M.; Raghuwanshi, N.S.; Singh, R.; Wallender, W.W.; Pruitt, W.O.: Estimating evapotranspiration using artificial neural network. J. Irrig. Drain. Eng. ASCE **128**, 224–233 (2002)
16. Kisi, O.; Ozturk, O.: Adaptive neuro-fuzzy computing technique for evapotranspiration estimation. J. Irrig. Drain. Eng. ASCE **133**, 368–379 (2007)
17. Dingman, S.: Physical Hydrology. Macmillan, New York (1994)
18. Fausset, L.V.: Fundamentals of Neural Networks: Architectures, Algorithms and Applications. Prentice Hall, Upper Saddle River (1994)
19. Neurosolution 5. Ward systems group, Inc., MD, USA (2008)
20. Garson, G.D.: Interpreting neural-network connection weights. Exp. Syst. Appl. **6**, 47–51 (1991)
21. Cook, D.F.; Ragsdale, C.T.; Major, R.L.: Combining a neural network with a genetic algorithm for process parameter optimization. Eng. Appl. Artif. Intell. **3**, 391–396 (2000)
22. Petridis, V.; Kazarlis, S.; Felelis, A.: A hybrid genetic algorithm for training neural networks. In: Proceedings of ICANNs 92, Brighton, pp. 953–956 (1992)
23. Odhiambo, L.O.; Yoder, D.C.; Hines, J.W.: Optimization of fuzzy evapotranspiration model through neural training with input–output examples. J. Transp. Eng. ASCE **44**, 1625–1633 (2001)