ESTIMATION OF REFERENCE EVAPOTRANSPIRATION BASED ON ONLY TEMPERATURE DATA USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Background: Evapotranspiration is an important component of the hydrological cycle, and the accurate estimation of this parameter is very important for many water resources applications. **Objectives:** The objective of this study was to estimate monthly reference evapotranspiration (ET_0) at Homs meteostation in Syria using artificial neural networks (ANNs) with minimal measured climate data such as the air temperature (maximum, minimum and average) used in this paper. **Methods:** The monthly reference evapotranspiration data were estimated by the Penman Monteith method, which is the sole standard method, and used as output of the neural networks. **Results:** The results of this study showed that feed forward back propagation Artificial Neural Networks (FFBP-ANNs) estimated successfully the monthly ET_0 using air temperature data, with low values of root mean square errors (RMSE), and high values of correlation coefficients (R). The result also showed that the using of the monthly index improves the accurate of estimation with correlation coefficient (R) of 99.7 %, and root mean square error (RMSE) of 7.28 mm/month for the test period. **Conclusions:** Thus, this research has shown the high reliability of artificial neural networks in estimation of monthly reference evapotranspiration at Homs meteostation using the air temperature data, and we can use these models in other places by adding the air temperature data in these places to the Homs meteostation's dataset and retraining the network again.
***Keywords**: Feedforward, Back Propagation, Penman Monteith, Monthly Index.*

1. INTRODUCTION

Evapotranspiration is an important component of the hydrologic cycle. It is combination of two separate processes whereby water is lost on the one hand from the soil surface by evaporation and on the other hand from the crop by transpiration [1].

The FAO-56 Penman Monteith (PM) is widely used for ET_0 estimation [2,3,4]. The empirical and statistical methods are also used in ET_0 estimation [5,6,7]. On the other hand, large number of researchers has been established the applicability of artificial neural networks (ANNs) to improve the accuracy of estimation of evapotranspiration. Trajkovic et al. (2003) studied the application of adaptive RBF (Radial Basis Function) networks to forecast $ET_{0,\ t+1}$ using only $ET_{0,\ t-11}$ and $ET_{0,\ t-23}$ values [8]. Trajkovic (2005) compared between four temperature-based approaches for estimation reference evapotranspiration [radial basis function (RBF) network, Thornthwaite, Hargreaves, and reduced set Penman–Monteith methods] as compared to the FAO-56 PM method. The result showed that the RBF network predicted FAO-56 PM ET_0 better than other methods at most locations in Serbia [9]. Zanetti et al. (2007) developed artificial neural network models to estimate reference evapotranspiration as daily values and average values of 3, 7, 15, 30 days using only the maximum and minimum air temperatures data [10].

Also, Landeras et al. (2009) compared between ARIMA and ANNs models for forecasting weekly evapotranspiration in the region of Alava situated in the Basque Country (northern Spain). The results showed that ARIMA and ANN models reduced the prediction root mean square differences with respect to the mean year model by 6–8%, and reduced the standard deviation differences by 9–16% [11]. Rahimikhoob (2009) examined the potential for the use of ANNs models to estimate the reference crop evapotranspiration (ET_0) based on maximum and minimum air temperature and extraterrestrial radiation data under humid subtropical conditions on the southern coast of the Caspian Sea situated in the north of Iran and compared the results with Hargraves equation results [12]. Koupai et al. (2009) investigated the utility of artificial neural networks (ANNs) for estimation of daily grass reference crop evapotranspiration (ET_0), and compared the performance of ANNs with the conventional methods (Penman, Penman-Monteith, Stanghellini and Fynn) used to estimate ET_0 in Greenhouse [13].
Laaboudi et al. (2012) examined the effectiveness of the use of artificial neural networks (ANN) for the evaluation of ET_0 using incomplete meteorological parameters [14]. Moasheri et al. (2012) used artificial neural networks for modelling of

evapotranspiration for grass plant of a farm in Mo'tamediyeh village in Neishabour town of the Razavi Khorasan province [15]. Khoshhal and Mokarram (2012) used multi-layer perceptron networks (MLP) for estimating Reference crop evapotranspiration in Iran [16]. Esmaeilzadeh and Sattari (2015) Compared between feed forward back propagation neural networks and genetic programming for estimate monthly ET_0 using combinations of climatic parameters [17].

Also, Literature reviews observed that the estimation and prediction models for evaporation are superior with neural networks as a new tool which can solve the more complex modeling problems [18,19].

2. MATERIALS AND METHODS

2.1 Study site & data availability

Monthly measured weather data for 30 years (from 1975 to 2004) were obtained from Homs meteostation (latitude 34° 45' N, longitude 36°43' E, elevation 82.9 m), which is located in the middle of Syria. This data consisted of 347 monthly observations of maximum and minimum air temperature (T_{max} and T_{min}), mean relative humidity (RH_{mean}), wind speed (U_2), bright sunshine hours (SH).

2.2 Artificial Neural Network: Artificial neural networks are a kind of black box; this means we do not know its structure but just regard its behavior in practice [20]. The basic computational units in a neural network are the neurons (or perceptrons), which are connected by weighted links called synapses passing signals from one neuron to another [21]. So, ANNs are an attempt at modeling the information processing capabilities of human nervous systems [22]. ANNs learn through experience with appropriate learning exemplars, not from programming [23].

There are two types of neural networks by the learning algorithm classification: Supervised learning and unsupervised learning, and by the structure classification, there are also two types of neural networks: Feed-forward networks and feedback networks [24]. Probably, the feed forward ANN is the most common neural network structure used in neural network problems [25].

In this study, maximum, minimum, and average air temperature data were employed as input variables. The monthly ET_0 values calculated by the PM method were used as target output. These data were divided into three datasets for training, validation and testing as 80:10:10 % respectively. A back-propagation algorithm was used to train the artificial neural networks. the number of hidden-layer neurons were found by using trial-and-error method.

2.3 FAO-56 Penman-Monteith Method: The FAO Penman-Monteith method is the sole standard method for the definition and computation of the reference evapotranspiration. It requires radiation, air temperature, air humidity and wind speed data. The PM equation is given by FAO irrigation and Drainage Paper No. 56 as Eq.(1) [1]:

$$ET_0 = \frac{0.408\cdot\Delta\cdot(R_n - G) + \gamma\cdot\frac{900}{T+273}\cdot u_2\cdot(e_s - e_a)}{\Delta + \gamma\cdot(1+0.34\cdot u_2)} \tag{1}$$

Where ET_0 is reference evapotranspiration mm.day^{-1}, Rn is the net radiation at the crop surface MJ.m^{-2}.day^{-1}, G is the soil heat flux density MJ.m^{-2}.day^{-1}, T is the mean daily air temperature at 2 m height C°, U_2 is the wind speed at 2 m height m.s^{-1}, e_s is the saturation vapour pressure kPa, e_a is the actual vapour pressure kPa, e_s-e_a is the saturation vapour pressure deficit kPa, Δ is the slope vapour pressure curve kPa.C°$^{-1}$, γ is psychrometric constant kPa.C°$^{-1}$.

2.4 Data Normalization: Before exporting the data to the artificial networks, they were scaled between the interval 0 and 1 using the following Eq.(2) [26]:

$$x_{norm} = 0.5\cdot\left(\frac{x_0 - \bar{x}}{x_{max} - x_{min}}\right) + 0.5 \tag{2}$$

Where x_{norm} is the normalized value, x_0 is the original value, $\bar{x}$ is the average value, x_{max} is the maximum value, x_{min} is the minimum value.

2.5 Models Evaluation: The comparison between different ANNs models was done by using two statistical indices: correlation coefficient (R) and root mean square error (RMSE), which are defined as Eq.(3) and Eq.(4) [27]:

$$R = \frac{\sum_{i=1}^{n}(y_i - \bar{y}).(\hat{y}_i - \bar{\hat{y}})}{\left[\sum_{i=1}^{n}(y_i - \bar{y})^2 . \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2\right]^{\frac{1}{2}}} \quad (3)$$

$$RMSE = \left[\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}\right]^{0.5} \quad (4)$$

Where n is the number of observations, y_i is the estimated using the artificial neural networks, $\hat{y}_i$ is the observed ET_0 (calculated by the PM method), $\bar{y}$ and $\bar{\hat{y}}$ are the average value for y_i and $\hat{y}_i$.

3. RESULTS

Monthly values of reference evapotranspiration (ET_0) were estimated by ANNs Models. The performance criteria for the best ANNs Models with different architecture are shown in table 1. It is revealed that the best suitable network has the architecture of (4,17,1) (Model D), which has one hidden layer of 17 neurons, and uses tan sigmoid activation function and Levenberg – Marquardt (LM) algorithm with root mean square error (RMSE) of 6.50, 8.11, 7.28 mm/month for training, validation and test periods respectively. Also, the table showed that tan sigmoid activation function is better than log sigmoid activation function. And that the using of one hidden layer ANNs is sufficient to give the highest precision. Performance of the (4,17,1) ANN model during the training, validation and test period is shown in figure 1, and the best validation performance of this network is at epoch 112, which gives the minimum mean squared error (MSE) during the validation period. In figures 2 and 3, the comparison between ET_0 estimated with FAO56 PM method and computed with ANN model during the training, validation and test periods. These figures showed the high compatibility between ET_0 estimated with FAO56 PM method and computed with ANN model. Correlation between ET_0 estimated with FAO56 PM and computed with ANN model during all periods are shown in figure 4, and correlation coefficients (R) equal 99.616, 99.576, 99.706% for training, validation and test periods respectively.

Table 1: The table presents the performance criteria obtained by the best ANNs models.

	Network architecture	Activation function	Train R %	Train RMSE mm/month	Validation R %	Validation RMSE mm/month	Test R %	Test RMSE mm/month
A	3-16-1*	tan sigmoid	96.597	19.20	96.044	22.54	93.624	25.43
B	3-17-1*	tan sigmoid	96.643	19.07	96.280	22.82	95.376	25.47
C	4-16-1**	log sigmoid	99.616	6.50	99.482	8.79	99.525	8.22
(D)	4-17-1**	tan sigmoid	99.616	6.50	99.576	8.11	99.706	7.28
E	4-9-9-1**	tan sigmoid	99.607	6.59	99.46	9.05	99.671	7.23

* The network has 3 inputs: (T_{max}, T_{min}, T_{av}) only.

** The network has 4 inputs: (T_{max}, T_{min}, T_{av}) with the monthly index.

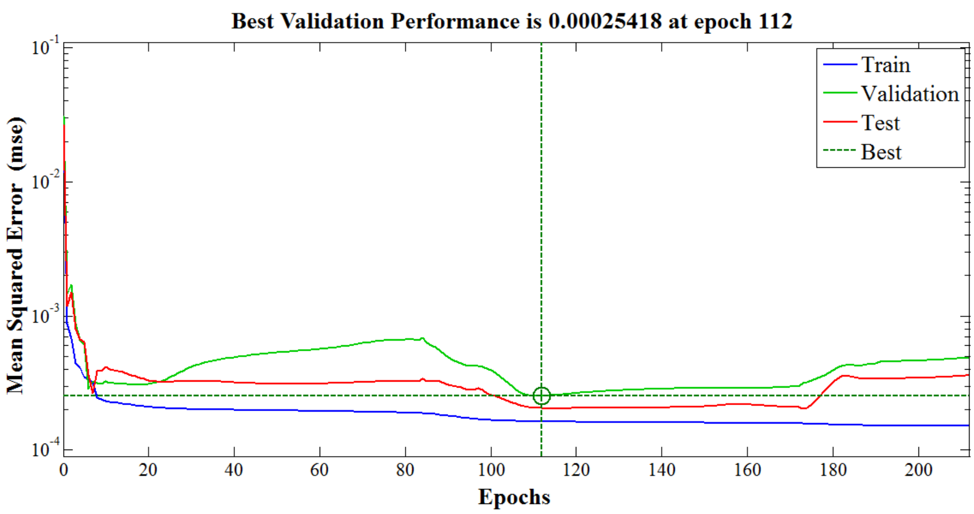

Figure 1: The figure presents the performance of the (4,17,1) ANN model during the training, validation and test period.

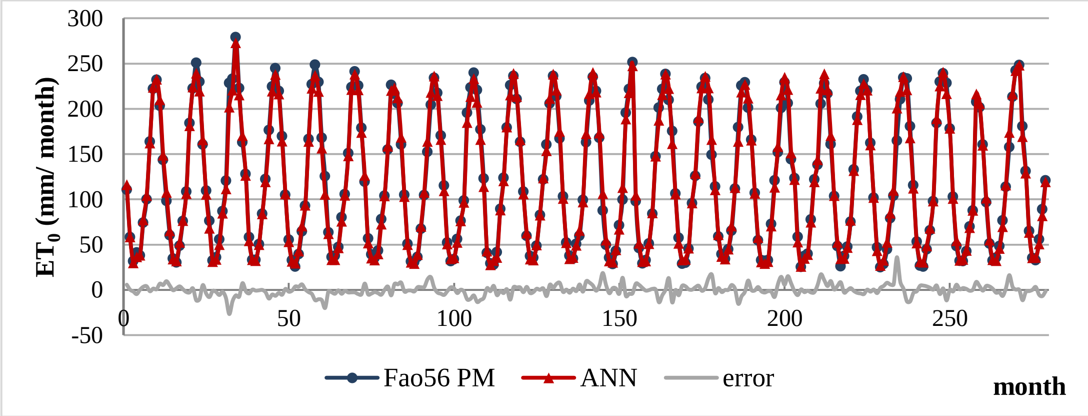

Figure 2: The figure presents comparison between ET_0 estimated with FAO56 PM method and computed with ANN model during the training period.

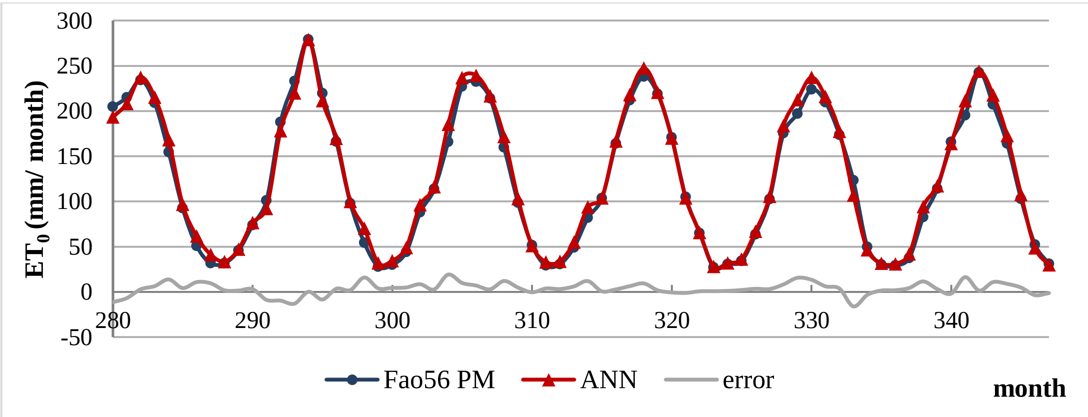

Figure 3: The figure presents comparison between ET_0 estimated with FAO56 PM and computed with ANN model during the validation and testing periods.

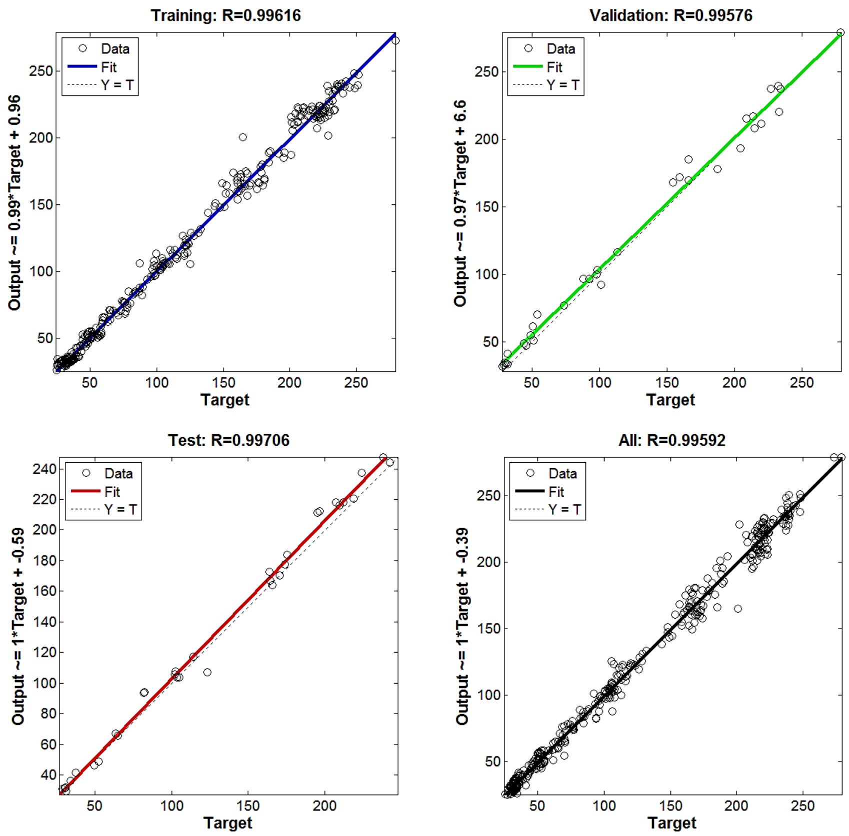

Figure 4: The figure presents correlation between ET_0 estimated with FAO56 PM and computed with ANN model during all periods.

4. DISCUSSION

In this study, artificial neural networks (ANNs) models were developed for estimating the monthly ET_0 at Homs meteostation by using as inputs the minimal meteorological data. These inputs include the monthly air temperature data (T_{max}, T_{min}, T_{av}) with the monthly index only. Because the air temperature is one of the most influential factors on evapotranspiration, and often available more than the other meteorological factors at Homs meteostation. The data were spilt into three datasets for training, validation and test in the ratio 80:10:10 respectively.

The neural networks were trained with 1–20 nodes in the hidden layer (or layers), with different activation function, training function and adaption learning function. After each training RMSE and R were calculated for training, validation and test periods to find the optimal number of hidden nodes using trial-and-error method. Feed forward backpropagation artificial neural network (FFBP ANN) was the best type of ANN models. The results showed that the using of the monthly index improves the accurate of estimation, and also showed that the best suitable network has one hidden layer of 17 neurons, which use tan sigmoid activation function and Levenberg – Marquardt (LM) algorithm with root mean square error (RMSE) of 6.50, 8.11, 7.28 mm/month for training, validation and test periods respectively, correlation coefficient (R) 99.616, 99.576, 99.706% for the same periods respectively. And for the all dataset RMSE was 6.75 mm/month, and R was 99.592%.

The result that we obtained in this research showed high precision estimations, and was better than the result of a lot of researches. For example, Rahimikhoob (2009) used three inputs which were the maximum and minimum air temperature and extraterrestrial radiation (RMSE=0.41 mm/day = 12.3 mm/month) [12], Zanetti et al. (2007) used four inputs which were the maximum and minimum air temperature and extraterrestrial radiation and the daylight hours (MSE=0.157 mm^2/day which equals 0.396 mm/day = 11.89 mm/month) [10]. Also, Koupai et al. (2009) and Laaboudi et al. (2012) depended, in their researches, on four inputs which were air temperature, relative humidity, wind speed and insolation duration (RMSE=0.86 mm/day = 25.8 mm/month) in the first research and (RMSE=0.27 mm/day = 8.1 mm/month) in the second research [13,14]. And also, Kumar et al. (2002) used six inputs which were solar radiation, maximum and minimum temperature, maximum and minimum relative humidity, and wind speed (Weighted Standard Error of Estimate WSEE=0.3 mm/day =9 mm/month) [26]. While in our research RMSE equals 7.28 mm/month. Although it is known that the precision will be better if we add a larger number of the meteorological factors and increase the number of neurons in the input layer, the results of our research were better of a lot of research which used larger number of meteorological factors than ours.

The final artificial neural network that we obtained can estimate the monthly ET_0 in Homs meteostation depending on air temperature data, and to make this model able to estimate ET_0 in other places we have to add the air temperature data in these places to the Homs meteostation's dataset and retraining the network again.

5. CONCLUSION

This paper presents the potential of artificial neural networks for the estimation of monthly reference evapotranspiration at Homs meteostation using minimal measured climatic data. The best artificial neural networks (ANNs) model containing only four inputs which are T_{max}, T_{min}, T_{av} (C^o) and the monthly index. The results showed that ANNs using air temperature data estimated the monthly ET_0 successfully and with high reliability. Such models have a very significant practical use, because they can be used when the other data are not available.

The results obtained suggested the realization of further evaluation studies of other types of artificial neural networks models for prediction of different climate variables.

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