Model for Prediction of Evapotranspiration Using MLP Neural Network

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ABSTRACT

Evapotranspiration is one of the main components of the hydrologic cycle. This complex process is dependent on climatic factors. There are different methods to predict Reference crop evapotranspiration. Artificial neural networks in recent decades, and studies for modeling complex systems and nonlinear features have shown ability very high. In this study multi-layer perceptron networks (MLP) were used for estimating Reference crop evapotranspiration. By using meteorological data between 2000 and 2010 stations of Eghlid plain in Iran was calculated the average values of evapotranspiration using the Penman-Monteith (PM). Then using these values as the output target, different networks with different structures were defined and taught. Finally, the network was evaluated to estimate evapotranspiration (Using part of the data are not used in the design of the network). By comparing the results of the ten networks was determined that MODEL 10 in the estimation of reference crop evapotranspiration is relatively more accurate.

Keywords: Evapotranspiration, Penman-Monteith, multi-layer perceptron networks.

1. Introduction

Evapotranspiration (ET) is a term used to describe the sum of evaporation and plant transpiration from the Earth's land surface to atmosphere. Evaporation accounts for the movement of water to the air from sources such as the soil, canopy interception, and waterbodies. Transpiration accounts for the movement of water within a plant and the subsequent loss of water as vapor through stomata in its leaves. Evapotranspiration is an important part of the water cycle. An element (such as a tree) that contributes to evapotranspiration can be called an evapotranspirator. (Jason A. et., al, 2010).

Evapotranspiration can be directly measured using of Lysimeter or be estimated with meteorological data. However, the not possibility of using lysimeter always be possible to measure evapotranspiration, because this method is time consuming and requires planning of accurate. Hence, indirect methods based on Weather data for estimating reference crop evapotranspiration has used. These methods include empirical equations or Methods based on physical processes of complex. One of the methods that are widely used to estimate evapotranspiration is the Penman-Monteith (Kumaret. al, 2002). According to research done, the Penman - Monteith is accurate methods of estimating evaporation and it can use for estimate transpiration and watering in different regimes. Artificial neural networks are a useful tool for modeling nonlinear systems. Artificial neural networks offer Simplified mathematical models of biological neuron networks (Basheer and Hajmeer, 2000). Recently, artificial neural networks (ANN) have been applied in meteorological and agroecological
modelling; most of the applications reported in literature concern estimation, prediction and classification problems [Arca et., al, 1998, Dowla and Rogers, 1995, Schultz et., al, 2000, Trajkovic et al., 2003; Keskin and Terzi, 2006; Parasuraman et al., 2007; Dogan, 2008; Kim and Kim, 2008]. Sudheer et al. (2003) and Zanetti et al. (2007). Neural network applications have diffused rapidly due to their functional characteristics, which provide many advantages over traditional analytical approaches. Recently, Khoob (2008a) and Landeras et al. (2008) used similar data set without the daily light to estimate successfully the evapotranspiration. In the study using an MLP neural network for prediction of evapotranspiration in Eghlid plain.

2. Case study

The study area, the Eghlid county, is located in the Fars province in Iran, between latitudes 27° 02' 00" N- 31° 42' 00" N and longitudes 50° 42' 00" E- 55° 36'00" E with an area of 133000 km² (Figure 1). Data used for the case study are consisting of: T_max, T_min, R_h, wind speed, sunshine hours and R_a in 470 locations. The numbers of points used in this study are 432 locations (Jahad Keshavarzi organization, 2009).

3. Methods

3.1. Penman–Monteith (PM)

Penman–Monteith (PM) equation for calculation of the ET-ref is given by Allen et al. (1998) as following:

\[
ET - ref = \frac{0.408 \cdot (R_n - G) + y(900/(T + 273)) \cdot e_s \cdot (e_s - e_a)}{2 + y(1 + 0.3 \cdot u_2)}
\]  

(1)

where ET-ref is the reference evapotranspiration (mm day⁻¹); R_n 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

![Figure 1: Location of the study area in the Iran](image-url)
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saturation vapour pressure deficit (kPa); \( \Delta \) is the slope vapour pressure curve (kPa °C\(^{-1}\)); \( \gamma \) is the psychometric constant (kPa °C\(^{-1}\)).

3.2. Multilayer perceptron network (MLPN)

In this paper, the MLPN consists of three-layers of neurons (input, hidden and output layer as shown in Figure. 2) interconnected by weights. The MLPN transforms \( n \) inputs to \( m \) outputs (also called input-output mapping) through some nonlinear function, \( f^* : \mathbb{R}^n \rightarrow \mathbb{R}^m \). The weights of the MLPN are solved or trained by the error backpropagation algorithm. The activation function for neurons in the hidden layer is the following sigmoidal function.

\[
\sigma(x) = \frac{1}{1 + \exp(-x)} \quad (2)
\]

The output layer neurons are pure summations of inner products between the nonlinear regression vector from the hidden layer and output weights. The MLPN requires no offline training. During on-line training, the MLPN starts with random initial values for its weights, and then computes a one-pass backpropagation algorithm at each time step \( k \), which consists of a forward pass propagating the input vector through the network layer by layer, and a backward pass to update the weights of the gradient descent rule. By trial and error, fourteen neurons in the hidden layer are optimally chosen for on-line identification. After having trained on-line for a period of time, the training error should have converged to a value so small that if training were to stop, and the weights frozen, then the neural network would continue to identify the plant correctly while the operating condition remains fixed; this means the NN is able to generalize well. Also, the training of NNs is said to have reached a global minimum when, after changing the operating conditions, as well as freezing the weights, the network’s response is still reasonably acceptable (Jung-Wook Par, et., al, 2005).

![Figure 2: multi-layer perceptron networks (MLP)](image)

Then in order to best network configuration determined was used to train and test several other input combinations represented in Table 1 in order to apprehend the potential input variables affecting the ET-ref process. This may help to understand the weather influence on ET-ref. MODEL (2) model has three input variables; minimum and maximum air temperature, and extraterrestrial radiation. The extraterrestrial solar radiation is not a collected data but determined for a certain day and location of the Allen et al. (1998) procedure. MODEL (1) and MODEL (2) are designed as temperature-based models presenting similar to the conventional methods selected in this study. The input structures of MODEL (3), MODEL (5), and MODEL (7) are formed by inserting sunshine, relative humidity and wind into the MODEL (1) combination, respectively. Then, the model of MODEL (2) integrating sunshine, relative humidity and wind is presented by MODEL (4),
MODEL (6) and MODEL (8), respectively. Finally, having both relative humidity and wind together into the MODEL (1) and MODEL (2) are illustrated by MODEL (9) and MODEL (10), respectively. The network was trained and tested for each combination summarized in Table 1.

<table>
<thead>
<tr>
<th>Model</th>
<th>Inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODEL (1)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, $R_a$</td>
</tr>
<tr>
<td>MODEL (2)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, Sun</td>
</tr>
<tr>
<td>MODEL (3)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, $R_a$, Sun</td>
</tr>
<tr>
<td>MODEL (4)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, $R_h$</td>
</tr>
<tr>
<td>MODEL (5)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, $R_a$, $R_h$</td>
</tr>
<tr>
<td>MODEL (6)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, Wind</td>
</tr>
<tr>
<td>MODEL (7)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, Wind</td>
</tr>
<tr>
<td>MODEL (8)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, $R_a$, Wind</td>
</tr>
<tr>
<td>MODEL (9)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, $R_h$, Wind</td>
</tr>
<tr>
<td>MODEL (10)</td>
<td>$T_{\text{min}}$, $T_{\text{max}}$, $R_a$, $R_h$, Wind</td>
</tr>
</tbody>
</table>

### 3.3. Data normalization

The data used in this study such as minimum and maximum air temperature, extraterrestrial radiation, wind velocity and relative humidity were normalized for preventing and overcoming the problem associated with the extreme values. The decadal ET-ref values were computed using the different estimation models enumerated above. Decade time scale has been reported by Doorenbos and Pruitt (1977) and Hargreaves (1994) as suitable to estimate ET-ref. According to Zanetti et al. (2007), by grouping the daily values into averages, the ET-ref may be estimated due to their higher stabilization. For data normalization, the input and output data were scaled in the range of [0 1] using the following equation:

$$Y_{\text{norm}} = \frac{Y_i - Y_{\text{min}}}{Y_{\text{max}} - Y_{\text{min}}}$$

where $Y_{\text{norm}}$ is the normalized dimensionless variable; $Y_i$ is the observed value of variable; $Y_{\text{min}}$ is the minimum value of the variable; $Y_{\text{max}}$ is the maximum value of the variable.

### 3.4. Models evaluation

This study carried out a multicriterion performance evaluation by using the root mean square (RMSE), mean absolute error (MAE) and coefficient of determination ($R^2$). These statistical criteria are used to evaluate the performance between the alternative ET-ref models and PM as given by the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|$$

$$R = \frac{\sum_{i=1}^{N} (y_i - \bar{y}) (\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N} (y_i - \bar{y})^2} \sqrt{\sum_{i=1}^{N} (\hat{y}_i - \bar{\hat{y}})^2}}$$
where $y_i$ represents the PM observed ET-ref, $\tilde{y}_i$ is the estimated $\text{Et}_{\text{ref}}$ for the $i$th values; $\bar{y}$ and $\tilde{y}_i$ represent the average values of the corresponding variable; $N$ represents the number of data considered. Additionally, a linear regression $y = \alpha_1 x + \alpha_0$ is applied for evaluating the performance of ET-ref estimation, where $y$ is the dependent variable (alternative models); $x$ is the independent variable (PM); $\alpha_0$ is the intercept; $\alpha_1$ is the slope.

4. Result

This study adopted a hidden layer for the model construction since it is well known that one hidden layer is enough to represent the ET-ref nonlinear complex relationship (Kumar et al., 2002; Zanetti et al., 2007). The determination of the processing elements in the hidden layer providing the best test results was the initial process of the training procedure. The first 10 MODEL (Table 2) were developed. In these ANN the input variables were chosen both on the basis of physical laws that describe the evapotranspiration phenomena (PM). The data set was divided into three sections: the first section, composed of 302 records collected in 2000, was used for training; the second, composed of 65 records collected in 2000, was used for testing; and the third, composed of 65 records collected in 2010, was used for validating the ANN. The performance of empirical models and of the ANN was evaluated calculating root mean square error (RMSE), as a measurement of how closely two independent data sets match; mean absolute error (MAE), determination coefficient ($R^2$) were calculated.

Comparison Penman–Monteith (PM) and 10 models produced by multi-layer perceptron networks shown in Figure 3.

Table 2: Summary of models statistical

<table>
<thead>
<tr>
<th>Model</th>
<th>Inputs</th>
<th>$R^2$</th>
<th>RMSE (mmday$^{-1}$)</th>
<th>MAE (mmday$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODEL (1)</td>
<td>$T_{\text{min}}, T_{\text{max}}, R_a$</td>
<td>0.298</td>
<td>0.791</td>
<td>0.543</td>
</tr>
<tr>
<td>MODEL (2)</td>
<td>$T_{\text{min}}, T_{\text{max}}, \text{Sun}$</td>
<td>0.387</td>
<td>0.674</td>
<td>0.498</td>
</tr>
<tr>
<td>MODEL (3)</td>
<td>$T_{\text{min}}, T_{\text{max}}, R_a, \text{Sun}$</td>
<td>0.380</td>
<td>0.568</td>
<td>0.510</td>
</tr>
<tr>
<td>MODEL (4)</td>
<td>$T_{\text{min}}, T_{\text{max}}, R_h$</td>
<td>0.424</td>
<td>0.448</td>
<td>0.448</td>
</tr>
<tr>
<td>MODEL (5)</td>
<td>$T_{\text{min}}, T_{\text{max}}, R_a, R_h$</td>
<td>0.570</td>
<td>0.354</td>
<td>0.346</td>
</tr>
<tr>
<td>MODEL (6)</td>
<td>$T_{\text{min}}, T_{\text{max}}, \text{Wind}$</td>
<td>0.610</td>
<td>0.298</td>
<td>0.218</td>
</tr>
<tr>
<td>MODEL (7)</td>
<td>$T_{\text{min}}, T_{\text{max}}, \text{Wind}$</td>
<td>0.650</td>
<td>0.260</td>
<td>0.130</td>
</tr>
<tr>
<td>MODEL (8)</td>
<td>$T_{\text{min}}, T_{\text{max}}, R_a, \text{Wind}$</td>
<td>0.890</td>
<td>0.146</td>
<td>0.049</td>
</tr>
<tr>
<td>MODEL (9)</td>
<td>$T_{\text{min}}, T_{\text{max}}, R_h, \text{Wind}$</td>
<td>0.980</td>
<td>0.128</td>
<td>0.041</td>
</tr>
<tr>
<td>MODEL (10)</td>
<td>$T_{\text{min}}, T_{\text{max}}, R_a, R_h, \text{Wind}$</td>
<td>0.989</td>
<td>0.062</td>
<td>0.038</td>
</tr>
</tbody>
</table>
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MODEL(6)

MODEL(7)

MODEL(8)

MODEL(9)
5. Conclusions

This paper discusses a research study conducted to develop ANN based models to estimate ET0 from limited climatic data. The results show that an ANN technique can be used successfully to estimate ET0 from climate data. These results have been obtained since neural networks perform well in when inputs are incomplete or affected by measurement error. These characteristic allow the neural networks to incorporate meteorological variables which the empirical models do not consider; moreover, neural networks can be used for local calibration of the empirical models. So ET-ref constitutes a key element of efficient management of agricultural water resources. Therefore, artificial neural network approach may open a new opportunity for rapid estimation of accurate ET-ref in Eghlid plain.

5. References


