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Comparison of Artificial Neural Network and Physically Based Models for Estimating of Reference Evapotranspiration in Greenhouse

[1]Abedi-Koupai, J., [2]Amiri M.J., [3]Eslamian, S.S.

[1,3]Associate Professor, Department of Water Engineering, Isfahan University of Technology
[2] Graduate Student, Department of Water Engineering, Isfahan University of Technology,
Isfahan, Iran.

Abstract: Evapotranspiration (ET) is one of the major components of hydrologic cycle. Accurate estimation of this parameter is essential for studies such as water balance, irrigation system design and management, and water resources management. Generally we used climate data for calculating evapotranspiration from indirect methods. This study investigates the utility of artificial neural networks (ANNs) for estimation of daily grass reference crop evapotranspiration (ET_0) and compares the performance of ANNs with the conventional methods (Penman, Penman-Monteith, Stanghellini and Fynn) used to estimate ETo in Greenhouse. In the present study, the meteorological variables including air temperature, solar radiation, wind speed and relative humidity were considered daily. The daily outputs from on four physical ET and artificial neural networks have been tested against reference evapotranspiration data computed by the lysimeter to assess the accuracy of each method in estimating grass reference evapotranspiration in greenhouse. The accuracy of ANNs is the best but the accuracy of the Penman equation is the worse for estimating daily evapotranspiration compared with the other equations. In ranking the equations, Stanghellini equation, Penman–Monteith and Fynn, equation ranked in a second, third and forth places, respectively. The results showed the ANNs, Penman and P-M models overestimated ET, while the Fynn and Stanghellini models underestimated ET. The efficiency values of Penman, Fynn, P-M, Stanghellini and ANNs were 0.68, 0.72, 0.86, 0.907 and 0.93 respectively.

Key words: artificial neural networks, Stanghellini equation, Penman–Monteith, Fynn

INTRODUCTION

Production of seedlings of several species and cultivation of ornamentals and vegetables in greenhouses in Iran occupies an area of approximately 6431 ha (Amiri, 2008). The need to provide fresh and good quality products during long periods throughout the year lead to the adoption of this technology, so protected cropping has become a very popular production system in horticulture. However, research is needed on irrigation management to establish the appropriate method to be used to estimate crop evapotranspiration (ET), to avoid the excess or deficit water application, with consequent impacts on nutrient availability for plants, soil salinity and groundwater contamination. Water use by crops is of increasing concern as demands for water are growing while supplies are not. Evapotranspiration (ET) is the total amount of water lost via plant transpiration and soil evaporation per unit soil area where a crop is growing, in the unit of L / T or $L^3 / L^2 T$ (Allen *et al.,* 1988). Reference evapotranspiration, ET_0 is often defined as the ET of a broad expanse of 0.10 to 0.15 m tall, cool season grass when the ET is not limited by soil water content. The ETo is used to quantify evaporative demand within a region and to estimate crop ET when the ETo is multiplied by a crop coefficient (Kc) factor to account for differences between the grass and crop ET (Allen *et al.,* 1988). Transpiration involves the movement of water from a soil medium into plant roots, up through stems into leaves, followed by evaporation from leaves into the atmosphere. Because it is difficult to separate plant transpiration from soil evaporation, and because larger plants lose water mostly through transpiration, evaporation and transpiration are generally grouped together as ET. Two essential driving forces for transpiration to occur are solar radiation and a vapor pressure gradient. If soil moisture is adequate, plant characteristics and local climatic factors determine the rate

Corresponding Author: Mohammad Javad Amiri, Department of Water Engineering, Isfahan University of
Technology, Isfahan, Iran
E-mail: amiriboogar@yahoo.com

of plant transpiration. Drainage lysimeters are one of the most accurate devices for directly measuring ET and calibrating ET equations, especially for container grown plants. The Stanghellini equation is generally used to estimate ET in greenhouse condition and estimating ET with this equation frequently results in good agreement with observed data from lysimeters (Mpusia, 2006). The evaporation process is strongly nonlinear in nature; some researchers should emphasize the estimation of relatively accurate evaporation in the research field using modeling techniques (Bruton *et al.*, 2000; Lindsey and Farnsworth, 1997; Xu and Singh, 1998). Sudheer *et al.* (2002) investigated the prediction of Class A pan Evaporation using the neural networks model. They used the neural networks 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 neural networks model. Kisi (2006) 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 to estimate the daily reference evapotranspiration. The purpose of this study is comparing the artificial neural networks and four physical ET models to predict reference evapotranspiration in greenhouse.

MATERIALS AND METHODS

Research Site and Operating Dates:

The experiment was carried out from 23 September 2007 to 23 September 2008 in Isfahan University of Technology, Iran. The geometric characteristics of the glasshouse are as follows: eaves height 3.5 m, ridge height 5 m, total width 10 m and length 20m. The local altitude is 1624.4 m with latitude $32^{\circ} 42'$ N, longitude $51^{\circ} 28'$ E, mean annual precipitation of 134 mm, mean annual temperature of 17° C and mean relative humidity of 38%. The glasshouse was built at north-south orientation, covered with a polyethylene film of 0.15 mm thickness. It was naturally ventilated with a single continuous roof vent and lateral windows were kept open during daytime. For measuring microclimate inside the glasshouse, air temperature was measured by Hobo pendant temperature light sensors (2No.) and relative humidity was measured by RH-sensor. Incoming solar radiation was measured by luxmeter which is placed at the center of glasshouse 0.15 m above the floor. The handy vane anemometer was used to measure daily wind speed at 2 m above ground level. Research data were collected during one year. In glasshouse we used three drainage lysimeters, 0.6 diameter and 1.1 depth, located on the southern side, which had the bottom and walls covered with a butyl rubber insulation sheet. The soil texture of the lysimeters was clay loam, containing 25% sand, 41% silt and 35 % clay. This artificial soil is widely used in the greenhouses of the region. Volumetric soil water content at field capacity (FC) and permanent wilting point of the soil were 0.39 and 0.22 cm^3/cm^3. The soil profile in the lysimeter reproduced that of the outside area described above down to 0.6 m, where a layer of gravel was placed on top of the butyl rubber sheet. The lysimeter soil depth was adequate as most of the growth and activity of roots for grass. The grass in lysimeter was regularly cut back to 10-15 cm in height.

Lysimeter:

Grass or reference evapotranspiration (ET_0) were measured in the drainage type lysimeters by the soil water balance approach using the following equation:

$$ET_0 = (SWC_{to} - SWC_{tl}) + I-D \tag{1}$$

Where:
($SWC_{to} - SWC_{tl}$) is the change in volumetric soil water content between two measurement dates, I and D are, respectively, the total volumes of applied irrigation water and collected drainage for the period under consideration. The amount of water per irrigation and the frequency of water application were controlled by tensiometers installed at the depth of l5 cm. Irrigation was started when the soil water potential reached -20 KPa at the depth of 15 cm. Drainage from the lysimeters was collected daily and applied irrigation water was measured with a water meter. To ensure that ET was not limited by excessive or reduced soil water content, irrigation was adjusted to allow for some drainage from the lysimeter most of the time.

Artificial Neural Networks:

Artificial neural networks (ANNs) have emerged as one of the useful artificial intelligence concepts used in the various engineering applications. Due to their massively parallel structure and ability to learn by example, ANNs can deal with nonlinear modeling for which an accurate analytical solution is difficult to obtain.

Artificial Neural Networks consist of the large number of processing elements with their interconnections. ANNs are basically parallel computing systems similar to biological neural networks. They can be characterized by three components: nodes, weights (connection strength), an activation (transfer) function.

ANNs modeling is a nonlinear statistical technique; it can be used to solve problems that are not amenable to conventional statistical and mathematical methods. In the past few years, there has been constantly increasing interest in neural networks modeling in different fields of hydrology engineering.

The basic unit in the artificial neural network is the node. Nodes are connected to each other by links known as synapses, associated with each synapse there is a weight factor. Usually neural networks are trained so that a particular set of inputs produces, as nearly as possible, a specific set of target outputs.

Feed-forward Propagation Neural Networks (FFNN):

The most commonly used ANNs model is the two-layer feed-forward ANNs. In feed-forward propagation neural networks architecture, there are layers and nodes at each layer. Each node at input and inner layers receives input values, processes and passes to the next layer. This process is conducted by weights. Weight is the connection strength between two nodes. The numbers of neurons in the input layer and the output layer are determined by the numbers of input and output parameters, respectively. In the present study, feed-forward artificial neural networks are used. The model is shown in Figure 1.

ET_0 Models Descriptions:

The following ET_0 models have been chosen for this research because of their wide acceptance in the estimation of ET in many greenhouses:

Stanghellini Equation:

Stanghellini (1987) revised the Penman–Monteith model to represent conditions in greenhouse, where air velocities are typically low (>1.0ms^{-1}). The Stanghellini model includes calculations of the solar radiation heat flux derived from the empirical characteristics of short wave and long wave radiation absorption in a multi-layer canopy (Prenger *et al.*, 2002; Stanghellini, 1987). The leaf area index (LAI, m^{2}m^{-2}) is used to account for energy exchange from multiple layers of leaves on greenhouse plants. The form of the equation is:

$$ET_O = \frac{2\,LAI}{\lambda} \frac{\Delta\left(Rn - G\right) + K_t\,\dfrac{VPD.\rho.Cp}{r_a}}{\Delta + \left(1 + \dfrac{r_c}{r_a}\right)} \qquad (2)$$

Where
ETo: reference evapotranspiration (mmday^{-1}).
LAI: is the leaf area index in (m^{2}m^{-2}).
K_t: is a time unit conversion factor which is equal 86400 sday^{-1}.
Δ: slope of the saturation vapor pressure-temperature curve (Pa °C^{-1}).
VPD: is the vapour pressure deficit(kPa).
G: soil heat flux (MJm^{-2} day^{-1}).
Rn: net radiation (MJm^{-2} day^{-1}).
ρ : air density (kgm^{-3}).
r_c: is the canopy resistance(sm^{-1}).
r_a : is the aerodynamic resistance(sm^{-1}).
λ : Latent heat of vaporization of water (MJkg^{-1}).
C_P : Air specific heat at constant pressure(MJkg^{-1}°C^{-1}).

Penman Equation:

Penman (1948), used energy balance to predict evaporation from crop surfaces. He accounted for the energy required for evaporation, and he also recognized the need to account for the aerodynamic energy (wind) required for the removal of water vapor from leaf surfaces. Thus his equation became known as the combination equation. The model was tested using well-watered grass as a reference crop. However, it did not include surface resistance and aerodynamic resistance adjustments for water vapor transfer. Resistances to heat

and water vapor transfer were differentiated between the external resistance, controlling the movement of vapor from the leaf surface to the free air, and the internal resistance, which is a function of the characteristics of the leaf cuticle layer and the stomata. The form of the equation is (Penman, 1948):

$$ET_O = \frac{1}{\lambda}\left(\frac{\Delta}{\Delta+\gamma}(Rn-G) + K_w \frac{\gamma}{\Delta+\gamma}(a_w + b_w u_2)(e_s - e_a) \right) \tag{3}$$

Where: Kw is a units constant (6.43 for ET_0 in mm day^{-1} and 0.268 for ET_0 in mm hour^{-1}), the a_w and b_w terms are empirical wind coefficients that have often received local or regional calibration. The values for a_w and b_w for the original Penman equation (Penman, 1948) were 1 and 0.537, respectively, for wind speed in ms^{-1}.

Penman–Monteith Equation:

Monteith (1965), independently accounted for surface and aerodynamic resistance in appraising evaporation rate. As a result, the so-called Penman-Monteith (P-M) equation was defined.The Penman–Monteith equation (Monteith, 1965) in the following form is used to estimate daily or hourly ET_0 for two reference surfaces (Monteith, 1965):

$$ET_O = \frac{1}{\lambda} \frac{\Delta(Rn-G) + K_t \dfrac{VPD.\rho.Cp}{r_a}}{\Delta + \left(1 + \dfrac{r_c}{r_a}\right)} \tag{4}$$

K_t is a time unit conversion factor (86400 sday^{-1} for ET_0 in mmday^{-1}, 3600 sday^{-1} for ET_0 in mmh^{-1}).

Fynn Equation:

Fynn (1993), used a derivation similar to Stanghellini's to achieve a combination equation for ET in a greenhouse. His equation is distinguished by using total net radiation rather than Stanghellini's modified radiation calculation. The Fynn equation is also different because it modifies only the vapor pressure term with the LAI since water vapor exchange occurs at all layers of the canopy, while the irradiative energy exchange only occurs in the top most layer. The form of the equation is (Fynn, 1993):

$$ET_O = \frac{2LAI\,\rho Cp \dfrac{(e_s - e_a)}{r_a} + \Delta(Rn-G)}{\lambda\gamma ri_c} \tag{5}$$

To evaluate the performance of these models in daily ETo estimates, between the predicted and measured evapotranspiration using the Class A pan method values, several performance criteria were used including regression analysis, agreement index (D), mean absolute error (MAE), maximum absolute error (MAXE), and efficiency (EF), as suggested by Willmott *et al.* (1985) and Zacharias *et al.* (1996). These criteria are defined as:

$$D = 1 - \frac{\sum_{i=1}^{n}(Oi - Ei)^2}{\sum_{i=1}^{n}\left(\left|E_i - \overline{O}\right| + \left|O_i - \overline{O}\right|\right)^2} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Oi - Ei\right| \tag{7}$$

$$MAXE = MAX\left(\left|O_i - Ei\right|\right) \tag{8}$$

$$EF = \frac{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2 - \sum_{i-1}^{n}\left(O_i - E_i\right)^2}{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2} \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(O_i - E_i\right)^2}{n}} \tag{10}$$

Where O_i = measured value; E_i = predicted value; and $\bar{O}$ = mean observed values.

RESULTS AND DISCUSSION

Artificial Neural Network:

In this study, ANNs model was performed with neuro solution software. 60 percent of the total data was randomized for as training data, 20 percent of the total data was randomized as testing performance and 20 percent was selected for cross validation performance. ANNs evaporation model with four input variables (air temperature, relative humidity, solar radiation and wind speed) are considered. For ANNs model, the number of hidden layers considered after trial and cross validation is two layers and number of hidden neurons is obtained five neurons, and the used functions for hidden and output layers are log sigmoid.

The Training Performance:

In neuro solution software, 60 percent of the total data was randomized for training data. This software does not need for standardized input layer, and training data was used ordinary in this performance. Table 1 shows a statistical analysis of the PE for training performance. According to Table 1, the best network with 2000 epoch has MSE = 0.0066

The Test Performance:

The testing performance applied a cross-validation method in order to overcome the over fitting data. The cross-validate method is not to train all of the training data until MSE was reached to the minimum amount, but is to cross-validate with the testing data at the end of each performance. The correlation coefficient and MSE values were used to judge the performance of ANNs for data. Actual and predicted values of efficiency were also plotted. Table 2 shows a statistical analysis of the reference evapotranspiration for the testing performance of ANNs. Table 2 shows that for cross validation, the values of D, EF and r-square (R^2) were 0.93, 0.85 and 0.92 respectively.

Comparison ANNs and four physical ET model:

The regression equations and the statistical coefficients obtained for each models are shown in Table 1. ANNs provided best estimates of ET and resulted in the higher value of EF, followed by Stanghellini, Penman–Monteith, Fynn, Penman. A possible reason of the better performance by ANNs may be that it has a larger number of user- defined parameters. ANNs and Stanghellini equation showed very good performance, with values of EF equal to 0.93 and 0.907, respectively. Performance of Penman–Monteith was also good, with EF equal to 0.86, while Fynn equation was used, results showed that this equation can not provide good estimation of ET inside the glasshouse.

Evapotranspiration values of the ANNs, Penman–Monteith and Penman were higher than the measured ET, where the ratios $ET_{Lysimeter}/ET_{ANNs}$, $ET_{Lysimeter}/ET_{Penman–Monteith}$ and $ET_{Lysimeter}/ET_{Penman}$ were 0.95, 0.91 and 0.65, respectively. Stanghellini and Fynn equations underestimated $ET_{lysimeter}$, where the ratios, $ET_{Lysimeter}/ET_{Stanghellini}$ and $ET_{Lysimeter}/ET_{Fynn}$ were 1.07 and 1.2, respectively. Figures 2 and 3 were plotted the actual and predicted values of reference evapotranspiration by ANNs and Stanghellini equation, that shows fitting of the measured and predicted values of reference evapotranspiration by ANNs and Stanghellini equation.

Table 1: Statistical analysis of the lysimeter for the training performance

Best Networks	Training	Cross Validation
Epoch #	2000	2000
Minimum MSE	0.00665413	0.006126789
Final MSE	0.00665413	0.006126789

Table 2: Statistical analysis of the reference evapotranspiration for testing performance

Test Performance	ET
D	0.95
MAE	0.65
MAXE	2.75
RMSE	0.86
EF	0.93
R^2	0.97

Table 3: Regression equation of difference methods compared to ET of Lysimeter)ETlysimeter(

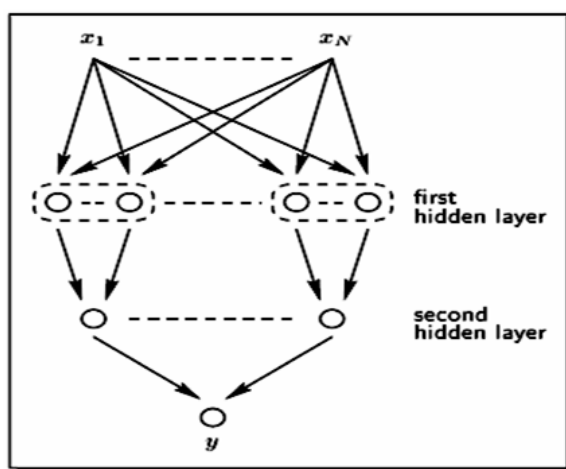| Method	Equation	Performance	EF	D	R^2
ANNs	ETLysimeter - 0.95 ET_{ANNs}	Very good	0.93	0.97	0.95
Stanghellini	ETLysimeter - 1.07 ET_S	Very good	0.907	0.94	0.93
Penman-Monteith	ETLysimeter - 0.91 ET_{P-M}	good	0.86	0.89	0.89
Fynn	ETLysimeter - 1.2 ET_F	Reasonable	0.72	0.76	0.87
Penman	ETLysimeter - 0.65 ET_P	Not good	0.66	0.71	0.81

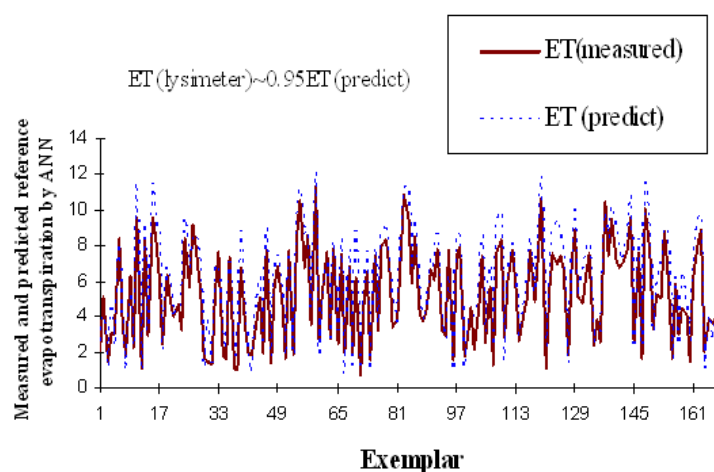**Fig. 1:** Feed-forward artificial neural networks with two layers

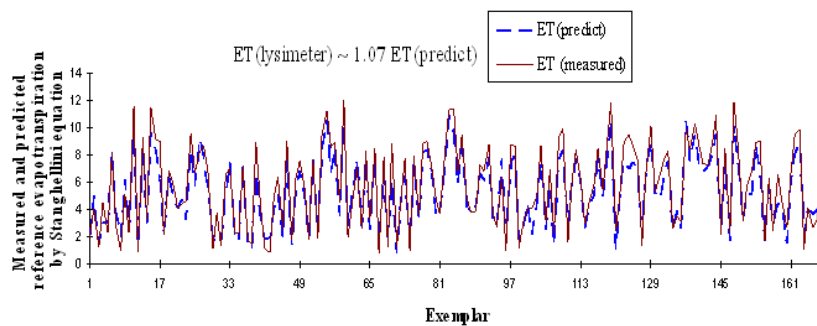**Fig. 2:** Predicted reference evapotranspiration using ANNs

Fig. 3: Predicted reference evapotranspiration using Stanghellini equation

Discussion:

Comparison of the r-square and efficiency values also suggests an improved performance by both ANNs and Stanghellini equation. Based on this study, both ANNs and Stanghellini equation approaches work equally well for the data set used. The computation cost involved with ANNs is significantly smaller than the Stanghellini equation. Based on these results, it can be concluded that the ANN can predict ETo better than the conventional method (Penman, Penman-Monteith, Stanghellini and Fynn) for greenhouse condition.

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