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EVAPOTRANSPIRATION- FROM CHANGED PERSPECTIVE

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ABSTRACT

The prior knowledge of evapotranspiration (ET_0) is crucial for estimating crop-water demand, preparation of water distribution schedules and water diversion. The present study investigates the utility of artificial neural networks (ANN) and lines a regression model (LRs) for forecasting ET_0 based on hydro-meteorological data. Based on different inputs, eight ANN and LR models are developed. The results are compared with those of FAO-56 Penman-Monteith expression. The published daily climatic data from the Oakville Station (Canada) are used to verify the effectiveness of the developed models. Based on various performance indices, ANN models are found predicting ET_0 more accurately than LR models. The best performing ANN model has parameters like previous day's evapotranspiration, relative humidity, average temperature, solar radiation and wind speed as inputs.

KEYWORDS: *Evapotranspiration, Penman-Monteith Expression, Ann Models, Agriculture*

INTRODUCTION

Evapotranspiration is a term used to describe the demands of evaporation and the plant transpiration. Evaporation accounts for the movement of water to the air from the sources such as soil, canopy interception, and water bodies, whereas, transpiration accounts for the movement of water within a plant and the subsequent loss of water as vapor through stomata in its leaves. Modeling evapotranspiration has always been an important issue for irrigation and agriculture engineers. Irrigation engineers require it for determining irrigation water quantity for designing the canals while agriculture engineers for knowing the specific water requirements of a crop so that they can obtain a satisfactory yield.

Numerous methods have been proposed for estimating evapotranspiration. The combination of energy balance/aerodynamic equations generally provides them accurate results as a result of their foundation in physics and basis of rational relationships [1]. The Food and Agricultural Organization of the United Nations (FAO) has accepted the FAO Penman-Monteith as the standard method for estimation of ET_0. However, the large data requirement of this method is its greatest demerit. On the other hand, soft computing techniques like artificial neural networks (ANNs) are gaining popularity for forecasting hydrological parameters because of their ability to model both linear and non-linear systems without the need to make assumptions as are implicit in most traditional approaches. This ability of ANN capture relationships from given patterns Has enabled them to be employed in various hydraulic and hydrologic problems such as modeling of river runoff [2,3], stream water level [4, 5], river flow [6–8], evapotranspiration [9], ground water table fluctuation[10,11], reservoir operation rule [12–14], dispersion coefficient prediction [15], only to name a few.

In this study, the potential of ANNs is examined in estimating the actual evapotranspiration from limited climatic data. We have selected neural networks in our study as these heuristics are particularly suited for modeling nonlinear, non-stationary and non- Gaussian processes like those seen countered in hydrological contexts. Linear regression has been included in this study as a yardstick to gauge the performance of ANN models because it is simple to develop and widely employed in hydrologic modeling.

ARTIFICIAL NEURAL NETWORKS

An artificial neural network involves a network of simple processing elements called neurons which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters. Artificial neurons were first proposed in 1943 by Warren McCulloch, a neurophysiologist, and Walter Pitts, an MIT logician. While a neural network does not have to be adaptive, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow. The process is known as training or learning. Training of an artificial neural network involves two phases. In the first phase or forward pass, the input signals propagate from the network input to the output. In the second phase or reverse pass, the calculated error signals propagate backward through the network, where they are used to adjust the weights. The calculation of the Output Is carried out, layer by layer, in the forward direction. The output of one layer is the input to then ex-layer. In the reverse pass, the weights of the output neuron layer are adjusted first for the target value of each output neuron is available to guide the adjustment of the associated weights. The weights on the output and hidden layer neurons can be calculated using Eqs. (1) and (2), respectively [16]:

$$w(N+1) = w(N) - \eta\delta\phi \tag{1}$$

$$w(n+1) = w(N) + \eta x \sum_{q=1}^{r} \delta_q \tag{2}$$

Where, x = input value; η=learning rate; ϕ= output; andδisdefinedas2ε_q δϕ/δI I, I being the sum of the weighted inputs, q= neuron index of the output layer, and ε_q=error signal.

The above training method is known as the standard back-propagation training method. Since back-propagation employs a form of gradient descent, it is assumed that the error surface slope is always negative and hence, constantly adjusting weights toward the minimum. However, error surfaces often involve complex, high dimensional space that is highly convoluted with hills, valleys, and folds. It is very easy for the training process to get trapped in a local minimum. The problem of the local minima can be avoided by adding a momentum term for the weight change to permit larger learning rates. The change of weight is then computed as follows:

$$\Delta w(N+1) = -\eta\delta\phi + \mu\Delta w(N) \tag{3}$$

Where μ = momentum coefficient and Δ*w* (*N* + 1) = change of weight during N *to N* + 1 learning cycles. Thus, the new value of weight becomes equal to the previous value of the weight plus the weight change, which includes the momentum term. This training method is known as back-propagation with momentum. A typical ANN structure with five inputs R, T, ET0, t−1, ET0, t−2 and ET0, t−3 are shown in Figure 1.

MODEL APPLICATION

Eight models, each of ANN and LR are developed for predicting evapotranspiration and their effectiveness evaluated on Oakville weather station (Canada). The predicted values of $ET_0$by these models are compared with those by FAO-56 Penman-Monteith expression, which is described by Allen *et al.* [1] As:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T-273}U_2(e_a - e_d)}{\Delta + \gamma(1 + 0.34U_2)} \tag{4}$$

Where = slope of the saturation vapor pressure function (kPa°C^{-1}); Rn= net radiation (MJ $m^{-2}day^{-1}$); G= soil heat flux density (MJ m^{-2} day^{-1}); c= psychometric constant (kPa°C^{-1}); T= mean air temperature (°C); $U2$ = average 24h wind speeds at 2m

The Oakville weather station is an automated weather station (Latitude 38° 26' 02" N, Longitude 122° 24' 35" W) operated by the California Irrigation Management Information System (CIMIS). Here, the total incoming solar radiation is measured using pyranometer at a height of 2.0 m above the ground. Air temperature is measured at a height of 1.5 m

Above the ground using a thermistor. Relative humidity is the ratio of the actual amount of water vapor in the atmosphere, to the amount the atmosphere can potentially hold at the given air temperature. The relative humidity sensor is sheltered in the same enclosure with the air temperature sensor at 1.5 m above the ground. Wind speed is measured using three- cup anemometers at 2.0 m above the ground. Twelve years (2000–2012) of these measured daily climatic data and the ET0 values calculated using the CIMIS Penman is downloaded from the CIMIS web server (http://wwwcimis.water.ca.gov). The data sample consists of daily records of solar radiation (Rs), air temperature (T), relative humidity (RH) and wind speed (U2). The first ten years (2000–2010) data are used for training and the remaining data are used for testing. Table 1 summarizes statistical information on the training (Table 1a) and testing (Table 1a) data sets for the Oakville station.

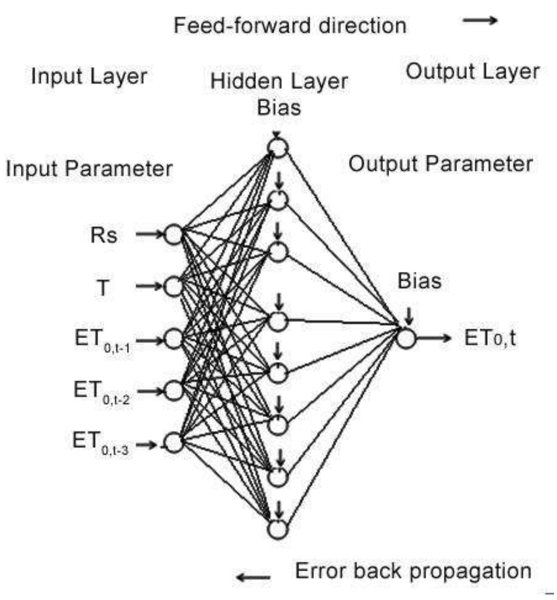

Figure 1: ANN Model Structure

Table 1: Statistical Parameters of Oakvile Station (Canada)

(a)

	Testing data(01/01/2000to31/01/2010)				
Parameters	**ET_0**	**Rs**	**T**	**U2**	**RH**
Unit	**mm/day**	**Ly/day**	**(°F)**	**MPH**	**(%)**
Maximum	8.382	784	77.2	9.3	97
Minimum	0	24	35.3	1.8	1
Mean	3.507	428	56.3	3.7	67
Std.deviation	1.9959	197	8.94	1.16	15.42
Range	8.382	760	41.9	7.5	96

(b)

	Testingdata(01/01/2011to23/07/2012)				
Parameters	**ET_0**	**Rs**	**T**	**U2**	**RH**
Unit	**mm/day**	**Ly/day**	**(°F)**	**MPH**	**(%)**
Maximum	8.382	784	77.2	9.3	97
Minimum	0	24	35.3	1.8	1
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Std.deviation	1.9959	197	8.94	1.16	15.42
Range	8.382	760	41.9	7.5	96

Eight ANN models, i.e., ANN1, ANN2, ANN3, ANN4, ANN5 ANN6, ANN7, and ANN8 are developed using different inputs (Table 2). The daily data of Rs, T, RH, U2, ET0, t−1, ET0, t−2 and ET0, t−3 were used in combination with each other as inputs to develop the most efficient ANN model for predicting evapotranspiration. The output in all models was ET0, t, i.e., the current-day evapotranspiration. The number of neurons in the hidden layer was changed from 1 to 20 neurons with the objective of minimizing the

Root mean square error (RMSE) between the measured and predicted evapotranspiration. A program code was written in MATLAB for simulation of the ANN model. To compare the results of ANN models, eight linear regression models, i.e., LR1, LR2, LR3, LR4, LR5, LR6, LR7 and LR8 with the same inputs as used in respective ANNs were developed. The statistical indices used for performance comparison of models are the mean absolute error (MAE), RMSE, correlation coefficient (CC) and discrepancy ration (DR) which are defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(ET_p - ET_o)^2} \tag{5}$$

$$CC = \frac{\left[\sum_{i=1}^{N} ET_p ET_o - \sum_{1}^{N} ET_p \sum_{1}^{N} ET_o\right]}{N S_p\ S_o} \tag{6}$$

$$\mathrm{DR} = \log\frac{ET_p}{ET_o} \tag{7}$$

Where *N* = the number of data, *ETp*, *ETo* are the predicted and observed evapotranspiration respective and *SS*, are the standard deviation of the predicted and observed *op* evapotranspiration respectively.

DR = 0 suggests exact matching between measured and predicted values; otherwise, there is either over prediction [DR > 0, i.e., *ETp* > *ETo*] or under-prediction [DR < 0, i.e., *ETp* < *ETo*].

RESULTS AND DISCUSSIONS

First, the developed ANN models are trained using daily data for ten years of the Oakville Weather Station. After training the networks satisfactorily, their performance is evaluated using another two years' data. The performance of the developed models is shown in Table 3.

The first model, ANN1/LR1 is formed with Rs, T, RH, and U_2as inputs. These meteorological Factors are known to affect ET considerably. As expected, solar radiation (Rs), air temperature (T), relative humidity (RH) and wind speed (U_2) is found adequate to predict the evapotranspiration as the model shows little deviation from the observed values having a very satisfactory CC and RMSE. In fact, ANN1outperformed all the other developed models with the minimum RMSE and the maximum coefficient of correlation between the observed and the predicted values of the current-day evapotranspiration. In models ANN2 and LR2, another input, the previous-day evapotranspiration, ET0,t−1, is added to see its effect on the performance of the neural network and linear regression models. As can be seen from Table 3, the LR model shows some improvement as its RMSE is slightly reduced from 0.317 to 0.310; however, there is no improvement in the value of CC. ANN model, on the other hand, deteriorates as its RMSE increases from 0.256 to 0.259 and CC decreases from 0.992 to 0.991. Other inputs, ET0, t−2 and ET0, t−3 are added to LR3/ANN3 and LR4/ANN4 models respectively. It is clear from Table 3 that the addition of inputs does not improve the performance of LR and ANN models. In simple models LR5 and ANN5, only RS and T are considered as inputs. But their performance is not satisfactory. They have the

Minimum Coefficient of Correlation and Maximum RMSE

Thus, in case of linear regression models, LR3model with Rs, T, RH, U2, ET0, t-1, ET Inputs has the best accuracy while among the neural network models, ANN1 with R, T, RH and U as input perform the best. Figure 2shows percentage of predicted values of evapotranspiration by the best ANN and LR models, i.e., ANN1 and LR3 falling in different discrepancy brackets. The figures show an even distribution of the predicted values around the ideal point, showing no tendency for over- or under-prediction. More than 67% predicted values have deviation less than 1% from the observed values, whereas

LR3 has less than 47% predicted values with the deviation less than 1%.

Table 2: Model Inputs

Model	Input
LR1/ANN1	R_S, T, RH and U_2
LR2/ANN2	R_S ,T, RH, U_2 and $ET_{0,t-1}$
LR3/ANN3	R_S ,T, RH, U_2, $ET_{0,t-1}$ and $ET_{0,t-2}$
LR4/ANN4	R_S ,T, RH, U_2, $ET_{0,t-1}$, $ET_{0,t-2}$ and $ET_{0,t-3}$
LR5/ANN5	R_S and T
LR6/ANN6	R_S ,T and $ET_{0,t-1}$
LR7/ANN7	R_S ,T, $ET_{0,t-1}$ and $ET_{0,t-2}$
LR8/ANN8	R_S ,T, $ET_{0,t-1}$, $ET_{0,t-2}$ and $ET_{0,t-3}$

Table 3: Performance Indices of Developed Models for Verification Dataset

Models	Model Inputs	RMSE(mm/day)		CC	
		LR	ANN	LR	ANN
LR1/ANN1	R_S, T, RH and U_2	0.317	0.256	0.988	0.992
LR2/ANN2	R_S,T, RH, U_2 and $ET_{0,t-1}$	0.310	0.259	0.988	0.991
LR3/ANN3	R_S,T, RH, U_2, $ET_{0,t-1}$ and $ET_{0,t-2}$	0.309	0.258	0.989	0.992
LR4/ANN4	R_S,T, RH, U_2, $ET_{0,t-1}$, $ET_{0,t-2}$ and $ET_{0,t-3}$	0.311	0.268	0.989	0.991
LR5/ANN5	R_S and T	0.375	0.350	0.982	0.985

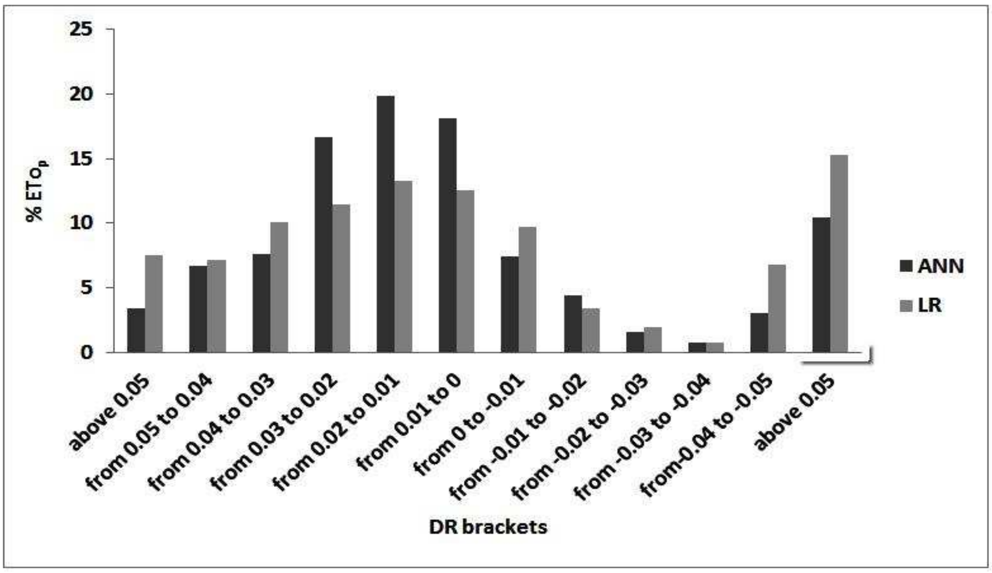

Figure 2

CONCLUSIONS

In the present work, the efficiency of ANN models in predicting evapotranspiration is investigated. Based on meteorological inputs, i.e., solar radiation, relative humidity, previous day's evapotranspiration, temperature and wind speed, five ANN models are developed. The developed models are evaluated using twelve-year data about Oakville Weather Station (Canada). Though all ANN models produce satisfactory results, the best ANN model is the one comprising input set of solar radiation, temperature, relative humidity and wind speed. This model predicted evapotranspiration closest to the measured values. For comparison purpose, five linear regression models are also developed.

ANN models are found superior to LR models. This is because the relationship between solar radiation, temperature, relative humidity, wind speed and evapotranspiration is an essential nonlinear, which is best captured by neural networks. The best performing ANN models predicted ET0 with the minimum RMSE of

0.256 mm/day and the maximum CC of 0.992,

Whereas the respective values of the best performing LR model are 0.309 mm/day and

0.989 Only.

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