

Estimation of Reference Evapotranspiration by Artificial Neural Network

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ABSTRACT: This study investigate the utility of artificial neural networks (ANNs) for estimation of reference evapotranspiration (ET_r) and compares the performance of ANNs with the conventional method Penman-Monteith model used to estimate ET_r. The ET_r estimated using Penman-Monteith method for growing season of pomegranate was compared with the results that occurred during training of artificial neural network (ANN) with feed forward backpropagation (BP) network having training function (TRAINLM), adaption learning function (LEARNGDM), performance function (MSE) and transfer function (TANSIG). Meteorological parameters such as minimum and maximum temperature, minimum and maximum relative humidity, wind speed and net radiation have been taken as input to network, and ET_r estimated by Penman-Monteith method for growing season of the pomegranate was considered as output of the network. The results reveals that, coefficient of correlation and mean square error between weekly and daily reference evapotranspiration (ET_r) estimated using Penman-Monteith method and ANN estimated ET_r for growing season of the pomegranate is 0.986 and 0.008618; and 0.999 and 0.00093, respectively.

KEYWORDS: Reference Evapotranspiration (ET_r), Penman-Monteith Model, Artificial Neural Network, Training, Testing, validation, correlation of coefficient, mean square error (MSE).

I. INTRODUCTION

Evapotranspiration is one of the major components of the hydrologic cycle and its accurate estimation is of paramount importance for many studies such as hydrologic water balance, irrigation system design and management, crop yield simulation and water resources planning and management. The estimation of evapotranspiration from vegetated surface is a basic tool to compute water balances and to estimate water availability and requirements, and a common procedure for estimating evapotranspiration from a well-watered agricultural crop is to estimate reference evapotranspiration from a standard surface or reference crop and then applies empirical crop coefficients.

Evapotranspiration can be either measured with a Lysimeter or water balance approach, or estimated from climatological data. However, it is not always possible to measure evapotranspiration with a Lysimeter because it is a time-consuming method and needs precisely and carefully planned experiments. Thus, indirect methods based on climatological data are used for ET_r estimation. These methods vary from empirical relationships to complex methods based on physical processes such as the Penman (1948) Combination method. The combination approach links evaporation dynamics with the flux of net radiation and aerodynamic transport characteristics of a natural surface. Based on the observations that latent heat transfer in plant stems is influenced not only by these a biotic factors, Monteith (1965) introduced a surface conductance term that accounted for the response of leaf stomata to its hydrologic environment. This modified form of the Penman equation is widely known as the Penman-Monteith evapotranspiration model. The reliability of Penman-Monteith method for estimating ET_r ranked as the best method for all climatic conditions [1] [2] whereas, ranking of other methods varied, depending on their local calibration and validation.

Evapotranspiration is a complex and nonlinear phenomenon because it depends on several interacting climatological factors, such as temperature, humidity, wind speed, radiation, type, and growth stage of the crop, etc. Artificial neural networks (ANNs) are effective tools to model nonlinear systems. A neural network model is a mathematical construct

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whose architecture is essentially analogous to the human brain. Basically, the highly interconnected processing elements (PEs) arranged in layers are similar to the arrangement of neurons in the brain.

In the past decade, considerable attention has been focused on the application of ANNs in diverse fields including system modeling, fault diagnosis and control, pattern recognition, financial forecasting, and hydrology. Studies on ANN application in the area of simulating the nonlinear hydrologic behaviour of watersheds (Hsu Kuo-lin *et al.*, 1993); soil water potential for different depths (Huien and Felker 1997; Altendorf *et al.*, (1999); pesticide concentration in the soil [5]; land drainage design [4] forecasting reference evapotranspiration [3]; river flow modelling during flood (Rajurkar *et al.*, (2004); and also in optimisation problems. Some of the studies [6] also have proved that ANN is more accurate than conventional methods. It is evident from the literature that ANN can be used in the prediction of ET with utilization of the input–output mapping capability of ANN.

Based on the capabilities, that ANNs have, to simulate nonlinearity among the interacting factors in the system, the present study is undertaken with the aim to estimate reference evapotranspiration with ANN and compared its performance with that of Penman-Monteith model describes the utilization of the input–output mapping capabilities of the ANN in ETr prediction.

II. REVIEW SURVEY

Artificial Neural Networks

An ANN consists of input, hidden, and output layers and each layer includes an array of processing elements. A typical neural network is fully connected, which means that there is a connection between each of the neurons in any given layer with each of the neurons in the next layer. A processing element is a model whose components are analogous to the components of actual neuron. The array of input parameters is stored in the input layer and each input variable is represented by a neuron. Each of these inputs is modified by a weight whose function is analogous to that of the synaptic junction in a biological neuron. The processing element consists of two parts. The first part simply aggregates the weighted inputs; the second part is essentially a nonlinear filter, usually called the transfer function or activation function. The activation function squashes or limits the values of the output of an artificial neuron to values between two asymptotes. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. On the other hand, to constrain the outputs of a network, the output layer should use as a sigmoid transfer function which is the most commonly used activation function. It is a continuous function that varies gradually between two asymptotic values, typically 0 and 1.

III. MATERIALS AND METHOD

Study area

The study carried out for Solapur district of Maharashtra which is under water scarcity zone having Latitude 17°40'N, Longitude 75°54'E and Altitude 484 m above mean sea level.

Data Collection

Meteorological data of 25 years (1983-2007): Daily parameters (i.e. maximum temperature (T_{max} , °C) and minimum temperature (T_{min} , °C), maximum relative humidity (RH_{max} , %) and minimum relative humidity (RH_{min} , %), pan evaporation (E_{pan} , mm), wind speed (WS, kmhr⁻¹) at height of 2.0 m, sun shine hours (SShr, hr), rainfall (R, mm)) etc. collected from Indian meteorological department, Pune.

Estimation of reference crop evapotranspiration with Penman Monteith Method

The most common FAO-56 Penman-Monteith equation was used for the estimating ETr for the present study. The daily values of ETr were calculated by given equation,

$$ET_r = \frac{0.408\Delta(R_n - G) + \gamma \left(\frac{900}{T + 273} \right) u_z (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_z)} \dots (1)$$

Where,

ET_r = reference evapotranspiration, (mm/day)

G = soil heat flux density, (MJ/m²/day)

R_n = net radiation, (MJ/ m²/day)

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T = mean daily air temperature, ($^{\circ}\text{C}$)

γ = Psychometric constant, ($\text{kPa}/^{\circ}\text{C}$)

Δ = Slope of saturation vapour pressure function, ($\text{kPa}/^{\circ}\text{C}$)

e_s = saturation vapour pressure at air temperature T, (kPa)

e_a = actual vapour pressure at dew point temperature, (kPa)

u_2 = average daily wind speed at 2 m height, (m/sec).

Artificial Neural Network Methodology

Artificial neural networks (ANNs) are a system basically modelled on the human brain. The field goes by many names, such as connectionism, parallel distributed processing, neuro-computing, natural intelligent systems, machine learning algorithms, and artificial neural networks. The network topology consists of a set of nodes (neurons) connected by links and usually organized in number of layers. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally non-linear operation on the result, and then outputs the final result. ANNs perform a particular function by adjusting the values of connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Most applications of neural networks fall into the following five categories: prediction, classification, data association, data conceptualization, and data filtering.

Back propagation Feed forward Network

Back-propagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. The term Backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. For multiple-layer networks we use the number of the layers to determine the superscript on the weight matrices. This network can be used as a general function approximator. It can approximate any function with a finite number of discontinuities, arbitrarily well, given sufficient neurons in the hidden layer.

Training

Once the network weights and biases have been initialized, the network is ready for training. The network can be trained for function approximation (nonlinear regression), pattern association, or pattern classification. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function.

Back propagation Algorithm

There are many variations of the Back propagation algorithm. The simplest implementation of Back propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly the negative of the gradient. In the reverse pass, the weights of the output neuron layer are adjusted first since the target value of each output neuron is available to guide the adjustment of the associated weights. Single iteration of this algorithm can be written as;

$$X_{k+1} = X_k + \alpha_k g_k \quad \dots (2)$$

Where

X_k is a vector of current weights and biases,

g_k is the current gradient and

α_k is the learning rate

Multilayer networks typically use sigmoid transfer functions in the hidden layers. These functions are often called squashing functions, since they compress an infinite input range into a finite output range. The purpose of the resilient back propagation training algorithm is to eliminate these harmful effects of the magnitudes of the partial derivatives.

Improving Generalization

The problem that occur during neural network training is over fitting. One method for improving network generalization is to use a network that is just large enough to provide an adequate fit. If the number of parameters in the network is much smaller than the total number of points in the training set, then there is little or no chance of over fitting. There are two methods for improving generalization that are regularization and early stopping. In this study to prevent the over fitting, the early stopping has been used.

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Pre-processing and Post Processing

Before training, it is often useful to scale the inputs and targets so that they always fall within a specified range. The function `premnmx` can be used to scale inputs and targets so that they fall in the range $[1, 1]$. If `premnmx` is used to scale both inputs and targets, then the output of the network will be trained to produce outputs in the range $[-1, 1]$. Another approach for scaling network inputs and targets is to normalize the mean and standard deviation of the training set. The vectors `meanp` and `stdp` contain the mean and standard deviations of the original inputs, and the vectors `meant` and `stdt` contain the means and standard deviations of the original targets. If `prestd` is used to scale both the inputs and targets, then the output of the network is trained to produce outputs with zero mean and unity standard deviation.

Principal Component Analysis

When the dimension of the input vector is large, but the components of the vectors are highly correlated (redundant), in this situation it is necessary to reduce the dimension of the input vectors. An effective procedure for performing this operation is principal component analysis. This technique has three effects: i) orthogonalizes the components of the input vectors (uncorrelated with each other); ii) orders the resulting orthogonal components (principal components) so that those with the largest variation come first; and iii) eliminate components that contribute the least to the variation in the data set.

Comparison of Reference Evapotranspiration (ET_r) Estimated using Penman-Monteith Method and ANN Technique

The reference evapotranspiration (ET_r) estimated using Penman-Monteith method for growing season of pomegranate was compared with the results that occurred during training of artificial neural network (ANN) with feed forward back propagation (BP) network having training function (TRAINLM), adaption learning function (LEARNGDM), performance function (MSE) and transfer function (TANSIG). Meteorological parameters such as minimum and maximum temperature, minimum and maximum relative humidity, wind speed and net radiation have been taken as input to network and reference evapotranspiration (ET_r) estimated using Penman-Monteith method for growing season of the pomegranate was considered as output of the network. The graphs have been drawn of error variation with each epoch of training, comparison between estimated values of ET_r using PM method and ANN estimated ET_r . The regression analysis between these two has also been made.

IV. RESULTS AND DISCUSSION

With the aim of study, to estimate reference evapotranspiration (ET_r) by artificial neural network model, the Feed forward network has been used with resilient back propagation method. Meteorological parameters such as minimum and maximum temperature, minimum and maximum relative humidity, wind speed and net radiation have been taken as input to network during training of reference evapotranspiration (ET_r) estimated using Penman-Monteith method and reference evapotranspiration estimated for growing season of pomegranate were considered as output of the network. The regression analysis has been done between actual and predicted values of ET_r on weekly and daily basis.

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1 Average Weekly ET, Estimated using Penman Monteith Method and ANN technique
Figure 1 shows, the error variation with each epoch of training;

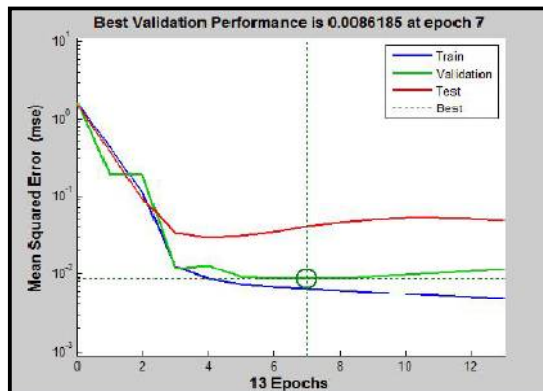


Fig. 1 Error variation with epoch/iteration of reference evapotranspiration (ETr)

Figure 2 shows, regression between training, testing and validation;

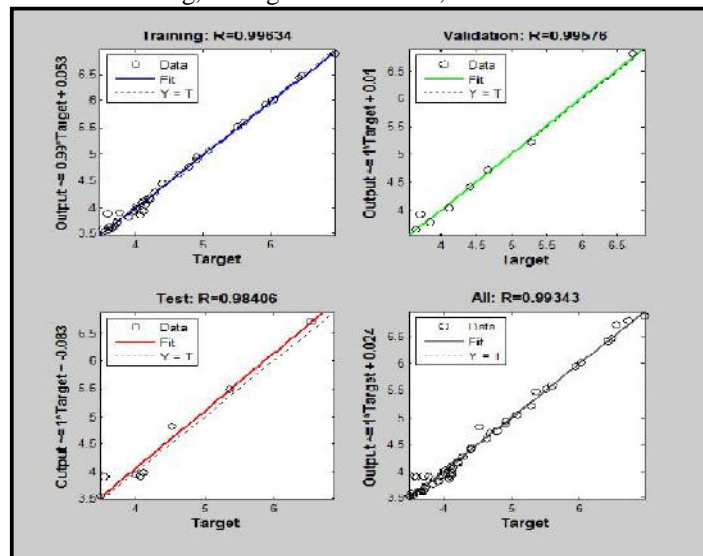


Fig.2 Regression between reference evapotranspiration (ETr) by Penman Monteith method and ANN technique for training, testing and validation

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Figure 3 shows, comparison between estimated ET_r using Penman-Monteith method

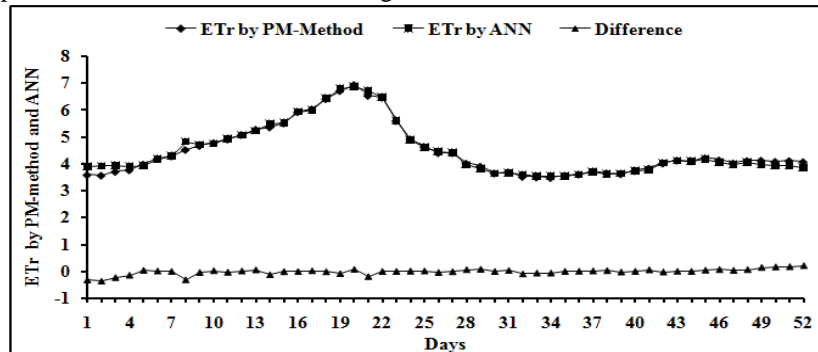


Fig. 3 Comparison between reference evapotranspiration (ET_r) by Penman Monteith method and ANN technique

and Figure 4 shows, ANN estimated; and regression analysis between these two values of ET_r for growing season of Pomegranate, respectively.

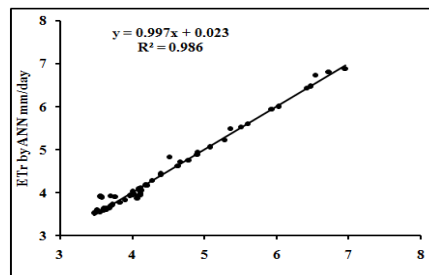


Fig.4 Regression analysis between reference evapotranspiration (ET_r) by Penman Monteith method and ANN technique

At the final point of training, after 16 epochs, mean square error was 0.008618 for 52 data sets (SMW-Standard Meteorological weeks). Figure 4 shows regression analysis between predicted and actual values of ET_r . The Coefficient of correlation was found to be 0.986. The equation of best-fitted line is $y = (0.997) x + 0.023$.

The results of training of ET_r with different number of neurons in hidden layer (3, 5, 7, 9, 11, 13, 15 neurons) estimated using Penman Monteith method for growing season of pomegranate is shown in Table 1. The best results are occurred during training of ET_r for growing season of pomegranate at 13 neurons in hidden layer and 16 epoch/iteration having minimum MSE 0.008618 and maximum coefficient of correlation 0.9934. The network with minimum MSE and maximum coefficient of correlation fits best.

Table 1 Comparison of average daily ET_r estimated by Penman Monteith method and ANN technique for different neurons in hidden layer

Number of data sets	Number of neurons in hidden layer	Epochs for final solution	Mean square error	Coefficient of Correlation
52	3	16	0.15738	0.8358
52	5	18	1.7548	0.7091
52	7	6	0.01314	0.9914
52	9	6	0.01147	0.9904
52	11	17	0.01034	0.9929
52	13	16	0.008618	0.9934
52	15	11	0.1610	0.9724

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2. Daily ET_r Estimated using Penman Monteith Method and ANN technique

Figure 5 shows, the error variation with each epoch of training;

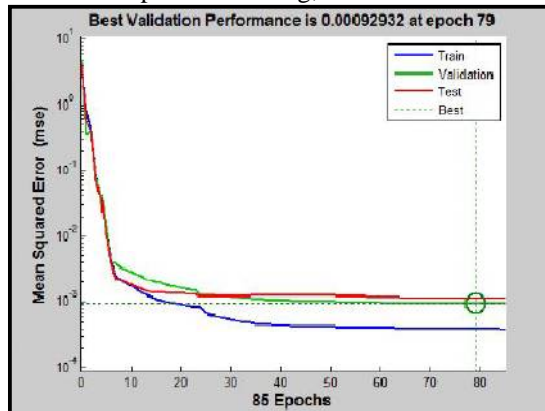


Fig. 5 Error variation with epoch/iteration of reference evapotranspiration (ET_r)

Figure 6 shows regression between training, testing and validation;

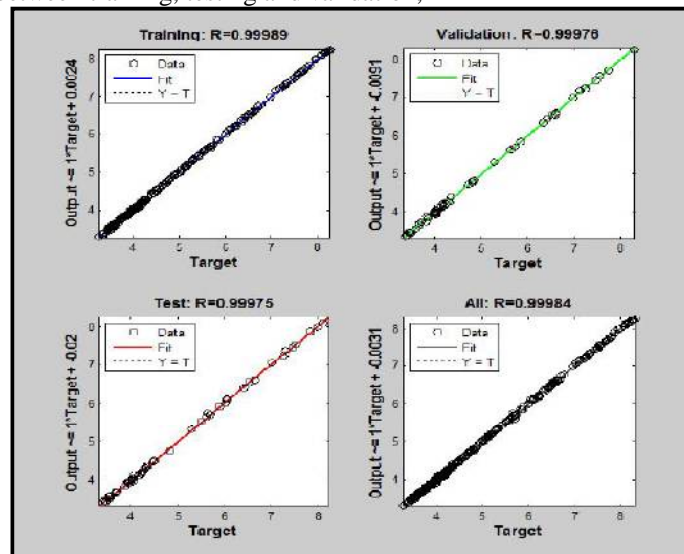


Fig. 6 Regression between reference evapotranspiration (ET_r) by Penman Monteith method and ANN technique for training, testing and validation

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Figure 7 shows comparison between estimated ET_r using Penman-Monteith method and ANN estimated and;

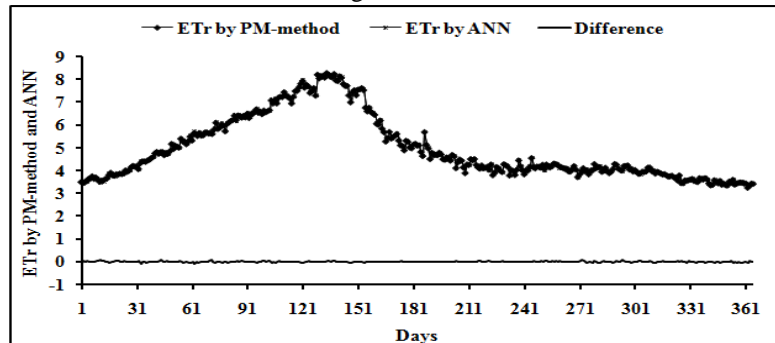


Fig. 7 Comparison between reference evapotranspiration (ET_r) by Penman Monteith method and ANN technique

Figure 8 shows regression analysis between these two values of ET_r for growing season of Pomegranate.

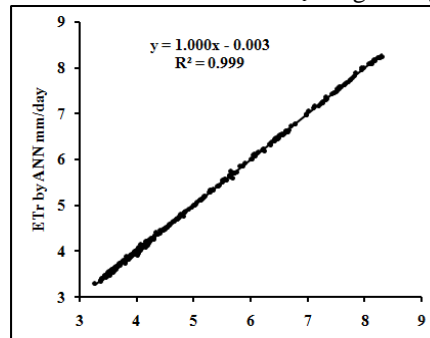


Fig.8 Regression analysis between reference evapotranspiration (ET_r) by Penman Monteith method and ANN technique

At the final point of training, after 85 epochs mean square error was 0.00093 using 365 data sets (Days of year) for the study. Figure 8 shows regression analysis between predicted and actual values of ET_r . The Coefficient of correlation was found to be 0.999. The equation of best-fitted line is $y = (1.000) x + 0.003$.

The results of training of ET_r with different number of neurons in hidden layer (5, 7, 9, 11, 13, 15 neurons) for growing season of pomegranate is shown in Table 2. The best results are occurred during training of ET_r for growing season of pomegranate is at 11 neurons in hidden layer and 85 epoch/iteration having minimum MSE of 0.00093 and maximum coefficient of correlation 0.9998.

Table 2 Comparison of daily ET_r estimated by Penman Monteith method and ANN technique for different neurons in hidden layer

Number of data sets	Number of neurons in hidden layer	Epochs for final solution	Mean square error	Coefficient of Correlation
365	5	160	0.00443	0.9861
365	7	36	0.01036	0.9972
365	9	26	0.00177	0.9997
365	11	85	0.00093	0.9998
365	13	35	0.00389	0.9951
365	15	28	0.00293	0.9962

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V. CONCLUSIONS

The results revealed that, the numerical analysis of reference evapotranspiration is easy and efficient. The coefficient of correlation between weekly and daily reference evapotranspiration (ET_r) estimated using Penman-Monteith method and ANN estimated ET_r for growing season of the pomegranate is 0.986 and 0.999, respectively and that of the MSE of estimated ET_r for growing season of the crops found 0.008618 and 0.00093, respectively that is very less.

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