Estimating Reference Crop Evapotranspiration using Neural Network Fitting



Engineering

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ABSTRACT

Evapotranspiration is a key parameter foragrometeorological studies and water resources management. This complex process is dependent on climatic factors. There are different methods to predict Reference crop evapotranspiration. In recent years, Artificial Neural Networks (ANN)have been applied as a powerful instrumentto increase predictability capacity of linear and nonlinear relationships in complex engineeringproblems. Use of this tool box in different fields of civil engineering, agriculture, environment, andin particular hydrologic matters for a range of significant parameters with complex mathematicalequations and variables have been addressed. In this studyneural network fitting tool is used for estimating Reference crop evapotranspiration. Meteorological data of Gandhinagarstationis collected to estimate reference crop evapotranspiration (ETo). Maximum and minimum temperature is used to develop the model. The estimated ETo by Neural Network is compared with ETo determined by Pan Evaporation Method. Coefficient of determination, Mean Square Error and Coefficient of correlations are used to evaluate the model. The study reveals that using ANN, ETo can be accurately predicted with limited climatological data for all months.

INTRODUCTION

Reference crop evapotranspiration (ETo) is one of the major components of the hydrologic cycle and its accurate estimation is important for many studies. ETo is a complex phenomenon because it depends on several interacting method and climatologic factors. But, it is not always possible to measure ETousing several methods because it is a time consumingand needs precisely and carefully planned experiments. Therefore the use of Artificial Neural Networks (ANNs) in estimation of reference evapotranspiration has received enormous interest in the present decade. It is a new way of computing artificial intelligence, which through different method is capable of managing the imprecision and uncertainties that appear when trying to solve problems related to real world, offering strong solution and easy implementation. Artificial Neural Networks are massively interconnected networks in which parallel of simple elements (usually adopted), with which try to interact with the object of the real world in the same way that the biological nervous system does.

The reference crop evapotranspiration (ETo) model is developed using the climatic data. The steps in the modelling include i) identification of metrological parameters influencing the region, ii) development of the model and iii) performance evaluation of the model development.

The present work is an attempt to study the Reference Crop Evapotranspiration through ANN ofGandhinagar, over the period of 9 years. From FAO-56, Pan Evaporation Method is used to compute the reference crop evapotranspiration values. For the prediction of Reference Crop Evapotranspiration it requires metrological data like Maximum and minimum Temperature, mean relative humidity, wind speed, sunshine hours, pan evaporation. MATLAB-R2009a software is used to predict the reference crop evapotranspiration by one of the tool named Neural Network Fitting Tool. For modelling, the data is divided in three sets, 60% data are used in Training, while 20% are used for testing and remaining 20% are for validation. Feed-Forward Back-Propagation method is used for this study.

Laaboudi et al. (2012) observed that the use of Artificial Neural Networks (ANNs) in estimation of Reference Crop Evapotranspiration has received enormous interest in the present decade. He described the Neural networks are proved to be parsimonious universal approximates of nonlinear function, and exploited this property to build various models in situation of lack of meteorological parameters and in different time steps. Trajkovic.S.,et al. used artificial neural networks for forecasting of reference evapotranspiration. Jain et al. developed a model to estimate ET using an artificial neural network (ANN) technique and to examine if a trained neural network with limited input variables can estimate ET efficiently. The results indicate that

even with limited climatic variables ANN can estimate ET accurately.

Study Area

Gandhinagar District is the administrative capital of Gujarat. The total area of the district is 2,163.48 sq. km. Gandhinagar has an average elevation of 81 metres (266 feet). The city sits on the banks of the Sabarmati River, in north-central-East Gujarat. The 20,543 km² area around Gandhinagar is defined by Gujarat capital Territory. The district has four Talukas, viz. Gandhinagar, Kalol, Dehgam and Mansa. Gandhinagar is divided into 30 sectors formed by roads laid in a rectangular grid with each sector having its own shopping, health, housing colonies and community centers. Gandhinagar is India's tree capital With 54% green cover on its land area.

Gandhinagar has dry climate with three main seasons: summer, monsoon and winter. The climate is generally dry and hot outside of the monsoon season. The weather is hot to severely hot from March to June when the maximum temperature stays in the range of 36 to 42 °C, and the minimum in the range of 19 to 27 °C. It is warm from December to February, the average maximum temperature is around 29 °C, the average minimum is 14 °C, and the climate is extremely dry. The southwest monsoon brings a humid climate from mid-June to mid-September. The average annual rainfall is around 803.4 mm (31.63 in).

Materials and Methods

Long-term meteorological data are collected from IMD (Indian Meteorological Department), Pune for Gandhinagar District of Gujarat. The basic meteorological data comprises of Maximum & Minimum Temperature (°C), Relative Humidity (%), Sunshine Hours (Hrs) and Wind Speed (kmph).

Reference Crop Evapotranspiration (mm/day) is calculated by Pan Evaporation method.

Artificial Neural Networks (ANN)

An Artificial Neural Network (ANN) model is composed of many artificial nodes that arelinked together. The objective is to transform the inputs into meaningful outputs. ANNshave the ability to learn by example and training. ANNs are nonlinear computationalframeworks based on the massive interaction with neurons, whose components have directanalogs to components of an actual human neuron. In general, the advantages of ANNs in comparison with statistical models are that (i) the application of ANNs does not require a prior knowledge of the process because ANNs have black-boxproperties, (ii) ANNs have the inherent property of nonlinearity since neurons activate anonlinear filter called an activation function, (iii) ANNs can have multiple inputs havingdifferent characteristics, which can make ANNs able to represent the time–space variability and (iv) ANNs have

the adaptability to represent change of problem environments.

Owing to these advantages, ANNs been used in numerous real-world applications. ANN was first introduced as a mathematical aid and was inspired by the neural structure of the brain. An input layer, which is used to present data to the network. An output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors. The ability of a neural network to process information is obtained through a learning process, which is the adaptation of link weights so that the network can produce an approximate output. In general, the learning process of an ANN will reward a correct response of the system to an input by increasing the strength of the current matrix of nodal weights.

There are several features in ANN that distinguish it from the empirical models. First, neural networks have flexible nonlinear function mapping capability which can approximate any continuous measurable function with arbitrarily desired accuracy, whereas most of the commonly used empirical model, do not have this property. Second, beingnon-parametric and data-driven neural networks impose few prior assumptions on the underlying process from which data are generated. Because of these properties, neural networks are less susceptible to model misspecification than most parametric nonlinear methods.

An ANN can be defined as data processing system consisting large number of simple highlyinterconnected processing elements (PEs or artificial neurons) in architecture analogous to cerebral cortex of brain. An ANN consists of input, hidden and output layers and each layer includes an array of artificial neurons. 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 neuron in next layer. An artificial neuron is a model whose components are analogous to the components of actual neuron in next layer. An artificial neuron 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 sometimes called synaptic weight) whose function isanalogous to that of the synaptic junction in a biological neuron. The neuron (processing element) consists of two parts. The first part simply aggregates the weighted inputs resulting in a quantity 1: the second part is essentially a nonlinear filter, usually cooed the transfer function or activation function. The activation function squashes or limits the values of the output of an artificial neuron to valuesbetween two asymptotes.

Neural Fitting Tool

In fitting problems, you want a neural network to map between a data set of numeric inputs and a set of numeric targets. Examples of this type of problem include estimating house prices from such input variables as tax rate, pupil/teacher ratio in local schools and crime rate (house_dataset); estimating engine emission levels based on measurements of fuel consumption and speed (engine_dataset); or predicting a patient's bodyfat level based on body measurements (bodyfat_dataset).

The Neural Network Fitting Tool will help you select data, create and train a network, and evaluate its performance using mean square error and regression analysis. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (newfit), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer.

The network will be trained with Levenberg-Marquardt backpropagation algorithm. (trainlm), unless there is not enough memory, in which case scaled conjugate gradient backpropagation (trainscg) will be used. During past couple of years, the Levenberg-Marquardt (LM), a second order optimization technique is extensively employed in evapotranspiration modeling using neural networks.

In the present study, the maximum and minimum temperatures are correlated with reference crop evapotranspiration determined by Pan Evaporation Method. Penman-Moientethequation

is the most accurate method but it requires all climatological data. Availability of all measured climatological data is major constraint in remote areas. An attempt is made to use limited climatological data to predict reference crop evapotranspiration using Neural Fitting tool Maximum and minimum temperature data are correlated with reference crop evapotranspiration for the period of 10 years. The whole data is divided into 70% for Training, 15% for Validation and 15% for Testing. For these datasets, correlations of input and output are observed using neural fitting tool. Then, the model is re-trained until the best coefficient of correlation is obtained and this corresponding model is considered as the best model .

Since the purpose of this study was the estimation of ETo, the ANN has only one output variable. The Pan Evaporationestimated mothlyETo values were employed as substitute for measured ETo data and used as target output. The number of hidden nodes in the ANN was determined empirically by trial and error, considering the need to derive reasonable results. Results obtained by both tools are evaluated by using two statistical indices: coefficient of correlation, R and Mean Square Error, MSE.

Coefficient of Correlation, R

Measure of the "goodness of fit" is the coefficient of correlation, R To explain the meaning of this measure, one has to define the standard deviation, which quantifies the spread of the data around the mean:

$$S_{t} = \sum_{i=1}^{n} \left(\overline{o} - o_{i} \right)^{2}$$

Where St is the standard deviation, oi is the observed data points and p is the average of predicted data points and the average the observed data points given by,

$$\overline{o} = \frac{1}{n} \sum_{i=1}^{n} o_{i}$$

The quantity St considers the spread around a constant line (the mean) as opposed to the spread around the regression model. This is the uncertainty of the dependent variable prior to regression. One also defines the deviation from the fitting curve as

$$S_r = \sum_{i=1}^n \left(O_i - P_i \right)^2$$

Where Sr is the deviation from the fitting curve, pi is the predicted data points.

$$R = \sqrt{\frac{s_t - s_r}{s_t}}$$

oFor Training

where R is defined as the coefficient of correlation. As the regression model starts improving describing the data, the correlation coefficient approaches unity. For a perfect fit, the standard error of the estimate will approach Sr = 0 and the correlation coefficient will approach R = 1.

RESULTS AND ANALYSIS Table - 1 Correlation coefficient, MSEand Discrepancy Rati-

INPUT	MONTH	R Training	MSE	Discrepancy ratio, (D)
Maximum temperature + Minimum temperature	January	0.95	0.10	0.94
	February	0.99	0.81	0.91
	March	0.99	2.96	0.92
	April	0.89	0.03	1.01
	May	1.00	0.68	0.98
	June	0.99	2.73	0.91
	July	0.99	0.23	1.00
	August	0.99	0.40	1.02
	Sept.	1.00	0.28	1.01
	October	0.67	0.21	0.99
	Nov.	1.00	0.08	1.12
	Dec	0.82	0.02	1.05

Table - 2Correlation coefficient, MSEand Discrepancy Ratio

for Validation

		R (Co-relation Co- efficient)		MSE	D
Input	Month	Testing	Validation		
Max. Temp. + Minimum Temp.	January	1.00	1.00	0.17	0.1
	Feb.	1.00	1.00	0.31	0.81
	March	1.00	1.00	0.25	2.96
	April	1.00	1.00	0.19	0.03
	May	1.00	1.00	0.25	0.68
	June	1.00	1.00	0.94	2.73
	July	1.00	1.00	0.60	0.23
	August	1.00	1.00	0.04	0.40
	Sep.	1.00	1.00	0.16	0.28
	October	1.00	1.00	0.18	0.21
	Nov.	1.00	1.00	1.12	0.08
	Dec.	1.00	1.00	0.10	0.02

In this study,input combination are taken as Maximum Temperature and Minimum Temperature. The value of R (Co-relation Co-efficient) ranges from 0.82-1.00 for all the months. R value for all the months are good except October and validation is also good for all months. This shows very good co-relation between the ETo by Pan Evaporation Method and ETo by ANN Method.

Evaluating Reference Crop Evapotranspiration taking this two input sets, we get MSE in the range of 0.02-0.81 except March and June. EvaluatingDiscrepancy ratio, (D) taking the Ratio of Mean of ETo by Pan Evaporation Method and ETo by ANN, we get D in the range of 0.91-1.05 which shows very good result for all the months. Fig. 1 to 5shows EToby Pan evaporation method and estimated by ANN for month of January, March, June, August and November.

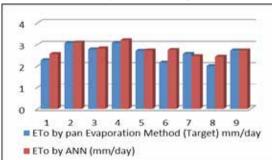


Fig.1 ETo by Pan evaporation method and estimated by ANN for month of January

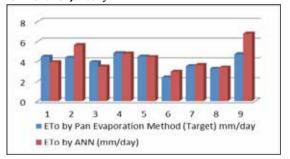


Fig.2 ETo by Pan evaporation method and estimated by ANN for month of March

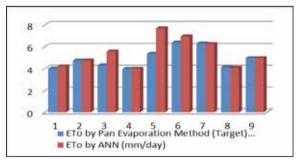


Fig.3 ETo by Pan evaporation method and estimated by ANN for month of June

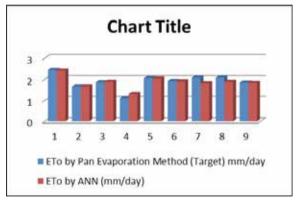


Fig.4 ETo by Pan evaporation method and estimated by ANN for month of August

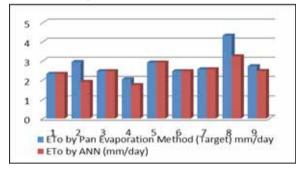


Fig.5 ETo by Pan evaporation method and estimated by ANN for month of November

CONCLUSIONS

- From the Result and Analysis it is concluded that except two months (March and June) ETo calculated by ANN is very close to Pan Evaporation Method, which reveals that using limited climatological parameters, ANN gives better results.
- R values and D values for this model are very close to 1. So this Model can be utilized for estimation of ETo.In this way ANN is very useful tool to estimate the ETo.

REFERENCE

[1]Abedi-Koupai et al (2009) "Comparison of Artificial Neural Network and Physically Based Models for Estimating of Reference Crop Evapotranspiration in Greenhouse" Australian Journal of Basic and Applied Sciences, 3(3): 2528-2535, 2009 | | [2] Laaboudi A. mouhouche B Draoui B (2011) "Neural network approach to Reference Crop Evapotranspiration modelling from limited climatic data in and regions" International Journal of Biometeorolgy, 56(5):831-41. | [3]Trajkovic, S., Todorovic, B., Stankovic, M., (2003), "Forecasting of reference evapotranspiration by artificial neural networks", Journal of Irrigation and Drainage Engineering 129 (6), 454-457. | [4]Sudheer, K.P., Gosain, A.K.and Ramasastri, K.S. (2003) "Estimating actual evapotranspiration from limited climatic data using neural computing technique", Journal of Irrigation and Drainage Engineering, ASCE, vol. 129, no. 3, pp214-218. |