Computers and Electronics in Agriculture 121 (2016) 385–392

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

An extreme learning machine approach for modeling evapotranspiration using extrinsic inputs

Amit Prakash Patil *, Paresh Chandra Deka

Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal, Mangalore, India

ARTICLE INFO

Article history:
Received 16 September 2015
Received in revised form 8 January 2016
Accepted 11 January 2016
Available online 2 February 2016

Keywords:
Evapotranspiration
Limited data
Extreme learning machine
Arid region
Least square support vector machine

ABSTRACT

Precise estimation of evapotranspiration is crucial for accurate crop-water estimation. Recently machine learning (ML) techniques like artificial neural network (ANN) are being widely used for modeling the process of evapotranspiration. However, ANN faces issues like trapping in local minima, slow learning and tuning of meta-parameters. In this study an improved extreme learning machine (ELM) algorithm was used to estimate weekly reference crop evapotranspiration (ETo). The study was carried out for Jodhpur and Pali meteorological weather stations located in the Thar Desert, India. The study evaluated the performance of three different input combinations. The first input combination used locally available maximum and minimum air temperature data while the second and third combination used ETo values from another station (extrinsic inputs) along with the locally available temperature data as inputs. The performance of ELM models was compared with the empirical Hargreaves equation, ANN and least-square support vector machine (LS-SVM) models. Root mean squared error (RMSE), Nash–Sutcliffe model efficiency coefficient (NSE) and threshold statistics (TS) were used for comparing the performance of the models. The performance of ELM model was found to be better than the Hargreaves and ANN model. The LS-SVM and ELM displayed similar performance. ELM3 models, with 36 and 33 neurons in hidden layer were found to be the best models (RMSE of 0.43 for Jodhpur and 0.33 for Pali station) for estimating weekly ETo at Jodhpur and Pali stations respectively. The results showed that ELM is a simple yet efficient algorithm which exhibited good performance; hence, can be recommended for estimating weekly ETo. Furthermore, it was also found that use of ETo values from another station can help in improving the efficiency of ML models in limited data scenario.

1. Introduction

Scarcity of water and growing need for food supplies emphasize on developing improved methods for crop-water estimation. As evapotranspiration (ET) plays a vital role in determining crop-water requirement, accurate estimation of evapotranspiration becomes evident. Besides, precise estimation of evapotranspiration is of great importance to many disciplines like hydrological studies, agriculture, meteorology and drainage studies. Considering the significance of accuracy in estimating evapotranspiration, hydrologists have mainly focused on developing more reliable and accurate methods for estimating evapotranspiration.

Evapotranspiration, is a very complex process which depends on the interaction of various atmospheric, plant and soil parameters. Generally, lysimeters are used for direct measurement of ET, but high operating costs and need for accuracy in measurements has limited the use of lysimeters (López-Urrea et al., 2006). Over the years, hydrologists have developed numerous physical, empirical and semi-empirical equations that used meteorological variables to estimate reference crop evapotranspiration (ETo). The Food and Agricultural Organization of United Nations (FAO) has accepted the FAO Penman–Monteith (FAO-56PM) as the standard equation to estimate ETo (Allen et al., 1998). The FAO-56PM is a physical based equation which offers best results in estimating evapotranspiration of living grass reference crop. Application of the FAO-56PM equation requires various meteorological variables like air temperature, solar radiation, humidity and wind speed. In developing countries like India, the network of weather stations capable of measuring all these parameters is sparse. However, small weather stations capable of measuring only few parameters like air temperature are ample in number. Therefore, there is an immediate need to develop a proficient ETo estimation system which can derive benefit from this set-up.

The Hargreaves equation is widely used as an alternative to FAO-56PM model in arid and semi-arid regions (Nandagiri and

* Corresponding author. Tel.: +91 7204858637.
E-mail address: amitpatil.nitk@gmail.com (A.P. Patil).

http://dx.doi.org/10.1016/j.compag.2016.01.016
0168-1699/

Kovoor, 2006). Hargreaves model estimates evapotranspiration as a function of maximum and minimum air temperature. Performance of this model highly depends on specific and complex relationships between temperature and ETo. Nevertheless, sometimes when other influencing factors like wind speed or humidity act predominantly the efficiency of Hargreaves equation is hampered. A model which uses locally available data together with evapotranspiration values from a place situated in the same climatic region may improve the efficiency of ET estimation where data are limited. Such a model may perform better as it can use data from weather stations capable of estimating ETo using FAO-56PM equation to model evapotranspiration of a place where only few climatic parameters can be recorded.

Recently, application of machine learning (ML) techniques (e.g., artificial neural network, adaptive neuro-fuzzy inference system and support vector machines) in modeling hydrological processes like evapotranspiration have received much attention from the researchers (Aksoy et al., 2007; Karimaldini and Shui, 2012; Kim and Kim, 2008; Kisi, 2011, 2006; Kumar et al., 2010; Partal and Kişi, 2007; Khoob, 2007; Shiri et al., 2013; Tabari and Talaee, 2012; Martí et al., 2015; Pour-Ali Baba et al., 2013; Shiri et al., 2015a, 2015b, 2014a, 2014b, 2014c). Machine learning algorithms provide explanation of an externally driven process without a need of complex physical models. Ease of experimentation, simple yet fast in the training and testing phases and low computational burden are some advantages of using ML techniques. Kisi and Cimen (2009) studied the potential of support vector machine (SVM) in modeling ETo for central California. They found that the SVM models can be effectively used for modeling ETo. Tabari et al. (2012) evaluated the performance of SVM, adaptive neuro-fuzzy inference system, regression and climate based models for modeling evapotranspiration. Kisi (2013) employed least square support vector machines (LS-SVM) to estimate daily ETo values. Wen et al. (2015) employed SVM to model ETo with limited climatic data in arid regions.

Artificial neural network (ANN) has been extensively used to model evapotranspiration due to its capabilities of capturing and representing complex input–output relationships without the detailed knowledge of process phenomenology. Kumar et al. (2002) used ANN for the estimation of ETo. Sudheer et al. (2003) employed radial-basis function (RBF) type ANN for computing the daily values of ET for rice crop. Zanetti et al. (2007) simplified the input variables used for the ANN and estimated ETo as a function of extra-terrestrial solar radiation, air temperature and sunshine hours. Aytek et al. (2008) proposed explicit neural network formulation for estimating reference evapotranspiration. The results were compared to five conventional ETo equations and a linear regression model. Chauhan and Shrivastava (2008) and Khoob (2010) used only maximum and minimum temperature datasets to estimate ETo. Kumar et al. (2008) compared the performance of different ANN models for arid and humid climates. Landeras et al. (2008) used various input combinations of meteorological variables for estimating evapotranspiration using ANN models. The performance of ANN models were compared to locally calibrated ETo models. Kumar et al. (2009) proposed generalized artificial neural network model for estimating ETo. Kisi (2009) compared the performance of two different ANN models. Martí et al. (2010a, 2010b) proposed ANN models with exogenous inputs. The models performed better than the existing temperature based models, which considered only local temperature data.

Generally, back-propagation (BP) algorithms are used to train ANN models. The BP algorithm needs iterative tuning to obtain optimal model parameter and may face issues like trapping in local minima, and are time consuming in learning. Additionally, building of an ANN model involves specification of several parameters like transfer function, learning rate, number of hidden layers and number of nodes in the hidden layer. Furthermore, the commonly used ANN applications treat these parameters as user defined functions. A non-expert user generally uses a trial and error method to set these parameters. Trial and error method does not always result into an optimum setting and may lead to low prediction accuracies despite using a good algorithm. Therefore, there is an immediate need to address these problems.

In this study an improved single layered feed forward neural network (SLFN) algorithm called extreme learning machines (ELM) is adopted to estimate weekly ETo. ELM algorithm does not need prior tuning of meta-parameters like input weights and hidden layer biases (Huang et al., 2012). This distinguishes it from the traditional neural network methodology. The ELM algorithm has exhibited promising results in some recent studies (Huang et al., 2011; Wang et al., 2011). Şahin et al. (2014) compared the performance of ELM to ANN model for estimation of solar radiation. The comparison showed that the ELM model gave better estimation than ANN model. Acharya et al. (2014) used ELM for estimating northeast monsoon rainfall over south peninsular India. Deo and Şahin (2015) employed ELM for prediction of effective drought index. Based on the results they concluded that ELM was an expeditious tool for prediction of drought.

This paper attempts to model the process of evapotranspiration in arid regions of India under limited data scenario. The primary objective of the study is to evaluate the capabilities of ELM to model the process of evapotranspiration. Further, results of the ELM model are compared to the well-established ANN and LS-SVM models. The secondary objective of the study is associated with input selection. Input parameters play a vital role in the performance of any ML based model. This study makes an attempt to evaluate the effectiveness of using locally available temperature data in conjunction with extrinsic ETo values for modeling the process of evapotranspiration.

2. Basics of ELM, ANN and LS-SVM

2.1. Extreme learning machines

The algorithms like BP during training of single-layer feed forward network (SLFN) use some rules to adjust the weights based on the given batch of training examples. On the other hand, weights are chosen randomly in ELM. Tamura and Tateishi (1997) and Huang (2003) found that SLFNs with randomly adopted input weights can efficiently learn distinct training examples with minimum error. On choosing the input weights and hidden layer biases the SLFN can be considered as a linear system and the output weights analytically determined by simple generalized inverse operation of the hidden layer output matrices. This simplified approach makes ELM work faster than the feed forward algorithm. The basic theory of ELM can be given as follows:

For M arbitrary distinct inputs (x_i, y_i) with $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$; a standard SLFN with N hidden nodes and activation function $\mathfrak{f}$ can be modeled as the following sum

$$\sum_{i=1}^{\mathcal{N}} \beta_i \mathfrak{f}(w_i x_j + b_i), \; j \in \{1, 2, 3, \ldots, M\} \tag{1}$$

where w_i are the input weights to the ith neuron in the hidden layer, b_i the biases and β_i are the output weights.

In the case where the SLFN would perfectly approximate the data, the relation is

$$\sum_{i=1}^{\mathcal{N}} \beta_i \mathfrak{f}(w_i x_j + b_i) = y_j, \; j \in \{1, 2, 3, \ldots, M\} \tag{2}$$

which can compactly be written as,