Journal of Hydrology 498 (2013) 36–45

Contents lists available at SciVerse ScienceDirect

Journal of Hydrology

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

Evolutionary neural networks for monthly pan evaporation modeling

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ARTICLE INFO

Article history:
Received 26 April 2013
Received in revised form 5 June 2013
Accepted 7 June 2013
Available online 14 June 2013
This manuscript was handled by Geoff Syme, Editor-in-Chief

Keywords:
Evaporation
Modeling
Differential evolution
Neural networks
Neuro-fuzzy
Stephens–Stewart method

SUMMARY

Estimating pan evaporation is very important for monitoring, survey and management of water resources. This study proposes the application evolutionary neural networks (ENN) for modeling monthly pan evaporations. Solar radiation, air temperature, relative humidity, wind speed and pan evaporation data from two stations, Antalya and Mersin, in Mediterranean Region of Turkey are used in the study. In the first part of the study, ENN models are compared with those of the fuzzy genetic (FG), neuro-fuzzy (ANFIS), artificial neural networks (ANN) and Stephens–Stewart (SS) methods in estimating pan evaporations of Antalya and Mersin stations, separately. Comparison results indicate that the ENN models generally perform better than the FG, ANFIS, ANN and SS models. In the second part of the study, models are compared with each other in estimating Mersin's pan evaporations using input data of both stations. Results reveal that the ENN models performed better than the FG, ANFIS and ANN models. It was concluded that monthly pan evaporations can be successfully estimated by the ENN method. The performance of the ENN model with full weather data as inputs presents 0.749 and 0.759 mm of mean absolute error for the Antalya and Mersin stations, respectively.

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1. Introduction

Evaporation, as a major component of the hydrologic cycle, has a vital importance in water resources development and management. Accurate estimation of pan evaporation is a crucial issue for monitoring, survey and management of water resources. Estimation of evaporation loss is imperative in the planning and management of irrigation practices in many areas where water resources are rare (Brutsaert, 1982; Jackson, 1985).

Engineers and researchers use loss from evaporation pans by multiplying by a pan coefficient, as an estimate of the evaporation loss from reservoirs. U.S. Weather Bureau Class A pan that is 4 ft in diameter and 10 in. deep and is assembled on a timber grill about 6 in. above the soil surface is the most commonly used pan. Pan evaporation is widely used as an index for evapotranspiration and for estimating evaporation from lake and reservoirs (Frevert et al., 1983; Irmak et al., 2002).

In the last decades, soft computing techniques (e.g., artificial neural networks, fuzzy and neuro-fuzzy systems) have been successfully used in modeling pan evaporation (Dogan et al., 2010; Keskin and Terzi, 2006; Kim et al., 2012, 2013; Kim and Kim, 2008; Kisi, 2005, 2006, 2009a,b,c; Kisi et al., 2012; Kisi and Tombul, 2013; Moghaddamnia et al., 2009; Nourani and Fard, 2012; Piri et al., 2009; Sanikhani et al., 2012; Shiri and Kisi, 2011; Sudheer et al., 2002; Tabari et al., 2010; Tan et al., 2007). Dogan et al. (2010) examined the accuracy of neuro-fuzzy (ANFIS) method for modeling of PE from the reservoir of Yuvacik dam in Turkey. Sudheer et al. (2002) used artificial neural networks (ANNs) to estimate pan evaporation (*PE*) and found that the ANN compares favorably to conventional approach. Keskin et al. (2004) used fuzzy models for estimating daily *PE* of western Turkey. Kisi (2006) investigated the accuracy of ANFISs technique in modeling daily pan evaporations. He found that the ANFIS computing technique could be successfully used in modeling evaporation process from the available climatic data. Keskin and Terzi (2006) developed ANN models for estimating daily *PE* and found that the ANN model performed better than the conventional method. Tan et al. (2007) estimated hourly and daily open-water evaporation rates using ANN technique. Moghaddamnia et al. (2009) examined the accuracy of ANN and ANFIS techniques in estimating *PE* in a hot and dry climate in Iran and compared them with the empirical methods. They found that the ANN and ANFIS techniques have much better performances than the empirical equations. Nourani and Fard (2012) investigated the sensitivity analysis of the ANN outputs in simulation of the *PE* at different climatologic regimes. Piri et al. (2009) modeled daily *PE* in hot and dry climate by ANN models. Kim et al. (2013) investigated different data-driven methods (e.g. ANN and ANFIS) in estimating daily *PE* in South Korea using different lag-time patterns. Kim and Kim (2008) applied ANN and genetic algorithm approach for non-linear modeling of *PE* and alfalfa reference evapotranspiration in Korea. Kisi (2009a) modeled daily *PE* using three different neural network techniques. Tabari et al. (2010) compared ANN and multivariate non-linear regression

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0022-1694/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jhydrol.2013.06.011

(MNLR) technique for modeling daily *PE* and found that the ANN performed better than the MNLR. Shiri and Kisi (2011) used ANN and ANFIS techniques for modeling daily *PE* by using available and estimated climatic data. Kisi and Tombul (2013) recently successfully applied fuzzy genetic approach for modeling monthly *PE* of Turkey. To the knowledge of the author, no study has been carried out to indicate the input–output mapping ability of evolutionary neural networks in pan evaporation modeling. This provided an impetus for the current investigation.

The accuracy of evolutionary neural networks (ENNs) for estimating pan evaporation using climatic variables is investigated in this study. The performance of the ENNs models are compared with those of the fuzzy genetic, neuro-fuzzy, ANN and Stephens–Stewart (SS) models employed in Kisi and Tombul (2013). This is the first study to compare the accuracy of the ENNs models with those of the FG models in the hydrological context.

2. Methodology

2.1. Artificial neural network

The artificial neural network (ANN) consists of one or more hidden layers and able to perform non-linear mapping between input patterns and target values. A three layered ANN structure is illustrated in Fig. 1. ANN is a massively parallel system and its network is composed of layers of parallel processing units called neurons, with each layer being fully connected to the proceeding layer by interconnection strengths or weights. During a training process (at each iteration), the initial assigned weight values are progressively corrected and the predicted outputs are compared with known outputs, and the errors are back-propagated to determine the appropriate weight adjustments which are necessary to minimize errors. The detailed theoretical explanation for the ANN and their applications within hydrology and water resources, have been thoroughly covered in a number of publications (e.g. Haykin, 2009; Maier and Dandy, 2000).

Some of the reasons that the ANNs have become an attractive computational tool are (ASCE, 2000): (a) They can recognize the relation between the input and output parameters without explicit physical consideration, (b) They are able to work well even when the training sets contain noise and/or measurement errors, (c) They can adapt to solutions over time to retrieve changing circumstances, (d) They have other inherent information-processing characteristics and once trained they are easy to use.

In the present study differential evolution algorithm was used for adjusting the weights of the ANN model. Detailed information about the differential evolution algorithm is given in the next section.

2.2. Differential evolution

Differential evolution (DE) is classified as a floating-point evolutionary optimization algorithm (Storn and Price, 1995, 1997; Lampinen, 2001).

Generally, the function to be optimized, *f*, is of the form

$$f(V): R^D \to R \tag{1}$$

where *R* refers to real numbers, and *D* is the number of parameters of the objective function, $f(V)$. The aim is to minimize the objective function $f(V)$ by optimizing its parameters' values

$$V = (v_1, \ldots, v_D), V \in R^D \tag{2}$$

where *V* is a vector consisted of *D* objective function parameters. In this study, the objective function $f(V)$ denotes the mean square error between the calculated and estimated PE values and v_i is the weights of the ANN (parameters). The parameters of the objective function respectively are subject to lower and upper boundary constraints, $v_i^{(L)}$ and $v_i^{(U)}$

$$v_i^{(L)} \leqslant v_i \leqslant v_i^{(U)} \quad i = 1, \ldots, D \tag{3}$$

As with all evolutionary optimization algorithms, differential evolution operates on a population, P_G, of candidate solutions, not just a single solution. The individuals of the population are composed of these candidate solutions. Differential evolution particularly maintains a population, and *G* is the generation to which the population belongs.

$$P_G = (V_{1,G}, \ldots\ldots, V_{\mathrm{NP,G}}) \quad G = 0, \ldots, G_{\max} \tag{4}$$

Each vector contains *D* real parameters (chromosomes of individuals):

$$V_{i,G} = (v_{1,i,G}, \ldots v_{D,i,G}) \quad i = 1, \ldots, \mathrm{NP}\ G = 0, \ldots G_{\max} \tag{5}$$

In order to set up a starting point for optimum seeking, the population must be initialized. In general, there is no knowledge available about the location of a global optimum other than the limits of the problem variables. A natural way to seed the initial population, $P_{G=0}$, is with random values selected from within the given limitations

$$V_{j,i,0} = \mathrm{rand}_j[0,1](v_j^{(U)} - v_j^{(L)}) + v_j^{(L)} \quad i = 1, \ldots \mathrm{NP}, \quad j = 1, \ldots, D \tag{6}$$

where $\mathrm{rand}_j[0,1]$ refers a uniformly distributed random value within the range: [0.0, 1.0] that is chosen for each new *j*.

Population reproduction scheme of the DE differs from other evolutionary algorithms. From the 1st generation onward, current population vectors, P_G, are randomly sampled and combined to create candidate vectors for the next generation,

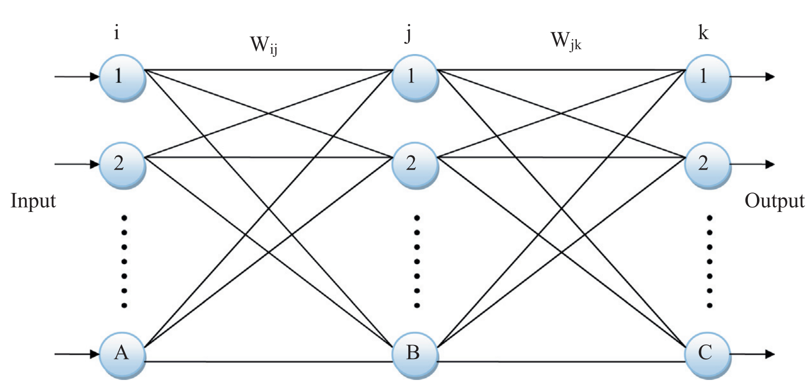

Fig. 1. A three-layer ANN architecture.

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