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Modeling global solar radiation using Particle Swarm Optimization (PSO)

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Abstract

The quantity of solar radiation received by the earth's surface is very important to numerous renewable energy applications. However, direct measurement of solar data is not widely available, especially in developing countries. This paper uses Particle Swarm Optimization (PSO) to train an artificial neural network (PSO–ANN) using data from available measurement stations to estimate monthly mean daily Global Solar Radiation (GSR) at locations where no measurement stations are available. The inputs to the networks are: month of the year, latitude, longitude, altitude, and sunshine duration, and the output is the monthly mean daily GSR at the specified location. Using training data from 31 stations and testing data from 10 locations, the PSO–ANN outperforms a neural network trained using the standard backpropagation (BP) algorithm (BP–ANN) with an average Mean Absolute Percentage Error (MAPE) of 8.85% for the PSO–ANN and 12.61% for the BP–ANN. The performance is improved significantly, when we use the leave-one-out method, where data from 40 locations is used for training and data from the 41st station is used for assessing the performance. In this case the average of MAPE on data from the 10 testing stations is about 7%. We used the same method to assess the performance of the PSO–ANN on testing data from each of the 41 stations with an overall average MAPE of about 10.3%. Comparison with BP–ANN and an empirical model showed the superiority of the PSO–ANN.

Keywords: Global Solar Radiation (GSR); Particle Swarm Optimization (PSO); Artificial Neural Networks (ANNs); Empirical modeling; Estimation

1. Introduction

The increasing cost of fossil fuel, uncertainty of its availability, and increasing environmental pollution encourage the utilization of green sources of energy. These energy sources include solar, wind, biomass, tidal, wave, ocean, and others. Solar and wind are the most commonly developed sources of green energy (Kammem, 2006). Although solar photovoltaic technology is more costly than other sources of green energy (Bull, 2001), it is used commonly to generate electricity for both stand alone and grid connected power systems (Liserre et al., 2010).

The quantity of solar radiation reaching the earth's surface is very important for numerous applications, such as electricity generation by means of photovoltaic cells, heating water using solar collectors, development of civil infrastructure, environmental and agro-meteorological research, and many other usages of solar energy resources. However, in spite of the wide range of applications requiring solar radiation, direct measurement of solar data is not widely available, especially in developing countries. The deficiency of measured data has prompted researchers to propose different methods and procedures including mathematical, statistical, neural networks, Markov chain, wavelets and others to estimate the needed solar data (Baños et al., 2011; Kalogrio, 2000; Zarzo and Martí, 2011). Sozen et al. (2004) used ANN approach for estimating the global

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solar radiation in spatial domains for the development of radiation maps for Turkey. They used latitude, longitude, altitude, sunshine duration and temperature from 11 stations for training an ANN model and data from 6 stations for testing the performance. Fadare (2009) developed an ANN model for predicting solar energy potential in Nigeria. He used data from 195 measurement stations for a period of 10 years (1983–1993). These measurements include latitude, longitude, altitude, mean sunshine duration, mean temperature, relative humidity, and month number. Tymvios et al. (2005) compared the outcome of various Ångström's type models with three artificial neural network models. The authors found minimum error between measured and predicted values of solar radiation from an ANN model with two inputs and one hidden layer of neurons. Mellit et al. (2005a) used an adaptive ANN to find a proper model for sizing stand-alone photovoltaic systems. Their model combined radial basis function (RBF) network and infinite impulse response (IIR) filter to improve convergence of the network. Mellit et al. (2005b) developed a hybrid model combining ANN with a library of Markov transition matrices to predict daily global solar radiation data in Algeria. The model achieved RMSE of less than 8% between measured and estimate GSR values using latitude, longitude, and altitude as inputs. In another study, Mellit et al. (2006) investigated the usage of adaptive wavelet-network architecture to predict the daily total solar radiation data. Their results indicated that the model predicted daily total solar radiation values with a maximum mean absolute percentage error of 6%. Poggi et al. (2000) used a Markov model to estimate hourly total solar radiation in Corsica. Behrang et al. (2011) used particle swarm optimization to obtain Angstrom coefficients to develop five new models for the estimation of solar radiation in Iran. They found that the empirical coefficients for a given latitude can be generalized to estimate solar radiation in cities at similar latitude. The performance of the developed models is measured by the mean absolute percentage error with values between 4.5% and 21.5%.

The Kingdom of Saudi Arabia (KSA) receives high intensity of solar radiation over extended hours of sunshine duration; hence solar energy based applications have excellent opportunities. Due to financial constraints, lack of human and technical resources, global solar radiation measurement is limited to 41 stations maintained by government organizations and other agencies. As a result of the limited measurement stations, a large number of research works have been done on model development for the prediction of global solar radiation as can be seen in (El-Sebaii et al., 2009, 2010; Mohandes and Rehman, 2010).

Artificial neural networks (ANNs) exhibit remarkable capability to learn any function from examples and apply this knowledge for unseen examples. The learning process of ANNs consists of two tasks: the selection of the network architecture, and the adjustment of the weights of the connection among the neurons. The most popular training algorithm to tune weights of the connections of a feed forward neural network is the backpropagation (BP) algorithm. The weights are adjusted in this algorithm relative to the difference between the network output and the desired output. The error propagates back from the output layer through the hidden layers to the input layer. The BP algorithm has been used extensively in many engineering applications. However, it suffers from slow convergence and getting stuck in local minima. Particle Swarm Optimization (PSO) has been proposed to overcome some of these problems (Kennedy and Eberhart, 1995; Kennedy, 1997; Shi and Eberhart, 1998; Abido, 2002). It has been motivated by the behavior of organisms such as bird flocking and fish schooling. Generally, PSO is based on a simple concept, computationally efficient, and easy to implement. It works by maintaining several candidate solutions in the search space. Each solution is considered as a particle moving through the search space. The fitness of each candidate solution is evaluated every iteration, and the best fitness value that it has achieved so far is remembered as its individual best fitness. The algorithm remembers also the global best fitness achieved by any particle and the candidate solution that achieved this fitness. Every iteration, the local and global bests are updated if better fitness values are achieved.

This paper is among the first attempts to use the PSO algorithm to spatially model monthly mean daily solar radiation values based on latitude, longitude, altitude, sunshine duration, and the month number. It should be noted that sunshine duration can be obtained from spatially continuous sunshine duration maps that are generated from geostationary satellite data (Good, 2010; Kandirmazm, 2006; Shamim et al., 2012). Data from 31 stations are used to train a neural network and the remaining 10 stations are used to evaluate the generalization performance of the developed network on data that has not been used in training. The performance of the PSO algorithm is compared favorably with the performance of the BP algorithms (Mohandes et al., 1998).

Moreover, to assess the generalization capability of the developed system when most of the available data is used for training the model, we evaluate the performance of 41 developed systems at all locations with known GSR using the leave-one-out method. Data from 40 locations are used to train an artificial neural network using the PSO algorithm (PSO–ANN) to estimate the GSR value at the 41st location. This process is repeated for all 41 locations. Results indicate good agreement between measured and predicted GSR values for most locations.

The rest of this paper is organized as follows: Section 2 discusses in details the PSO algorithm and Section 3 shows the implementation set up. Section 4 discusses the results, and Section 5 concludes the paper.

2. Particle Swarm Optimization (PSO) algorithm

PSO was introduced by Kennedy and Eberhart (1995) as a result of motivation by the behavior of bird flocking,