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The optimized artificial neural network model with Levenberg–Marquardt algorithm for global solar radiation estimation in Eastern Mediterranean Region of Turkey

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ABSTRACT

An accurate knowledge on global solar radiation is particularly required for proper placement and design of solar energy conversion systems. While the meteorological data are measured at most of the weather stations, global solar radiation measurement is not always performed due to high cost of the measurement devices and their operation and maintenance requirements. Therefore, several linear, non-linear and soft computing models are developed to estimate the solar radiation owing to being more economical when compared to installing pyranometers and these models provide satisfactory results. However, it is crucial to choose the most appropriate model for a specific purpose and region. The primary objective of this study is to optimize the performance of the artificial neural network model in order to realize an efficient estimation of solar radiation for Eastern Mediterranean Region of Turkey. Estimation performances are discussed for different structures of neural network by taking into account the number and quality of input features, learning algorithms, number of hidden neurons, correlation between network outputs and targets, and statistical error analysis methods. The presented model indicates that the artificial neural network models illustrate promising in the estimation of monthly mean daily global solar radiation by using commonly available data. In order to indicate the superiority of the performance of the model, it is evaluated with various test years, which are not used for training stage of the model. The presented model provides superior relationship between the estimated and measured values. The test results showed that the coefficient of determination and mean absolute percentage error between the optimized artificial neural network estimations and measured values for testing datasets are higher than 99% and %5, respectively.

1. Introduction

Accurate design and construction of solar energy systems needs a complete knowledge of the accessibility and variability of solar radiation intensity (Mecibaha et al., 2014). Output energy of photovoltaic (PV) modules is estimated by utilizing meteorological data. Global tilted irradiance data is needed to estimate output energy of PV modules (Yoshida et al., 2013) or calculation of diffuse radiation reaching PV system is essential for simulation of PV systems (Mondol et al., 2008). Measured data is manifestly the best data for proper knowledge of global solar radiation. Unfortunately, while sunshine duration data is extensively measured in almost all meteorological stations for long measuring period, it is not possible to measure global solar radiation in many areas due to cost, maintenance and calibration requirements of the measurement devices (Teke et al., 2015). Therefore, solar radiation prediction techniques have become a very important topic. There are many kinds of solar radiation prediction techniques that processing different meteorological parameters such as geographical parameters (latitude, longitude and elevation of the site) and meteorological parameters (extra-terrestrial solar radiation, sunshine duration, temperature, precipitation, relative humidity, effects of cloudiness, soil temperature, evaporation, reflection of the environs, etc.) are available in the literature. Since the records of these parameters are more readily available around the globe, these values are widely used to estimate the global solar radiation (Yadav and Chandel, 2014). Solar energy includes extraterrestrial solar

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Table 1
Input variables used in ANN to predict solar radiation.

Model	Input variable(s)	Study area	Learning algorithm	Output variable	R or R^2
Rahimikhoob (2010)	Temperature data (T_{max} and T_{min}) and the extraterrestrial radiation	Southwest of Iran	LM	Daily global solar radiation	0.8890
Sozen et al. (2004)	Latitude, longitude, altitude, month, mean sunshine duration and mean temperature	Turkey	LM, SCG, PCG	Solar potential in Turkey (monthly data are used)	0.9989
Fadare (2009)	Latitude, longitude, altitude, month, mean sunshine duration, mean temperature and relative humidity	Nigeria	LM, SCG	Monthly global solar radiation	0.9710
Benghanem et al. (2009)	Air temperature, relative humidity, sunshine duration and day of the year	Al-Madinah (Saudi Arabia)	LM	Daily global solar radiation	0.9765
Elminir et al. (2007)	Temperature, relative humidity, wind speed and wind direction	Egypt	BP	Daily and hourly diffuse fraction	0.9770
Koca et al. (2011)	Latitude, longitude, altitude, month of the year and mean cloudiness	Mediterranean region of Anatolia in Turkey	BP	Monthly global Solar radiation	0.9978
Behrang et al. (2010)	Day of the year, daily mean air temperature, relative humidity, sunshine hours, wind speed and evaporation	Dezful (Iran)	LM	Daily Global solar radiation	0.9957
Agbo et al. (2012)	Average temperature and relative humidity	Onitsha (Nigeria)	–	Daily Global solar radiation on horizontal surface	Different statistical tests performed
Ozgoren et al. (2012)	The global solar radiation and other meteorological parameters, like long-wave atmospheric emission, air temperature, relative humidity and atmospheric pressure.	Turkey	LM	Monthly mean daily sum global solar radiation	0.9936
Rehman and Mohandes (2008)	Day of the year, relative humidity and daily mean temperature	Abha (Saudi Arabia)	BP	Daily global solar radiation	Different statistical tests performed
Sfetsos and Coonick (2000)	Temperature, pressure, wind speed and wind direction,	Corsica (France)	LM, BP	Hourly solar radiation	Different statistical tests performed
Mubiru and Banda (2008)	Sunshine duration, maximum air temperature, cloud cover and location parameters: latitude, longitude, altitude	Uganda	LM (gives the best result among the used learning algorithms)	Monthly average daily global solar radiation received by a horizontal surface	0.9740
Qin et al. (2011)	Difference between daytime and night time land surface temperature, mean land surface temperature, precipitation, enhanced vegetation index, the number of days, ratio of the local air pressure and the one at sea level	Tibetan Plateau	SCG, Bayesian Regularization (BR)	Monthly mean daily global solar radiation	0.89–0.99
Mohandes et al. (1998)	Latitude, longitude, altitude and sunshine duration	Kingdom of Saudi Arabia	BP	Monthly mean daily global solar radiation on horizontal surface	Different statistical tests performed
Amrouche and Pivert (2014)	Meteorological forecasts	Le Bourget du Lac, Cadarache (France)	BP	Daily global horizontal solar irradiation at the surface	Different statistical tests performed
Dorvlo et al. (2002)	Month of the year, latitude, longitude, altitude and sunshine ratio	Oman	BR	Monthly global solar radiation	Different statistical tests performed

energy which is above the atmosphere and global solar energy which is under the atmosphere (Khatib et al., 2012).

Solar energy modeling techniques are classified as linear, nonlinear and artificial neural network (ANN) models and also revealed that the most accurate methods for prediction of solar radiation were ANN models (Khatib et al., 2012). The most popular estimation models are analytic, stochastic, empirical and ANN models (Mubiru and Banda, 2008). Many solar radiation estimation models are being developed for monthly basis readings (Qazi et al., 2015; Lin and Pai, in press). There are also new approaches ANN provides a computationally efficient way of determining an empirical, possibly nonlinear relationship between a number of inputs and one or more outputs (Benghanem et al., 2009). ANNs, which are increasingly receiving attention in solving complex practical problems, are known as universal function approximators. They are capable of approximating any continuous non-linear functions to arbitrary accuracy (Kémajou et al., 2012). Neural networks are used to estimate global solar radiation by many researchers as a function of climatic variables. The measured temperature data is used as an input to examine the potential of global solar radiation and compared the model with Hargreaves and Samani equation and achieved 0.89 as coefficient of determination (R^2) (Hasni et al., 2010). Latitude (lat), longitude (long), altitude (alt), month, mean sunshine duration and mean temperature were used as an input layer of the network whereas solar radiation as the output layer to estimate the solar potential in Turkey. They used the Scaled conjugate gradient (SCG), Pola–Ribiere conjugate gradient (PCG) and Levenberg–Marquardt (LM) learning algorithms and a logistic sigmoid transfer function in the network. Absolute mean percentage error (MAPE) was found as 0.04398 and R^2 was found as 0.99 (Sozen et al., 2004). Meteorological and geographical data were used (latitude, longitude, altitude, month, mean sunshine duration, mean temperature and relative humidity) as input layer of network while the solar radiation intensity was used as the