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Modeling of global horizontal irradiance in the United Arab Emirates with artificial neural networks

Hassan A.N. Hejase [a,*], Maitha H. Al-Shamisi [a], Ali H. Assi [b]

[a] UAE University, Department of Electrical Engineering, Al-Ain, United Arab Emirates
[b] Lebanese International University, Department of Electrical and Electronic Engineering, Beirut, Lebanon

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ABSTRACT

This paper employs ANN (Artificial Neural Network) models to estimate GHI (global horizontal irradiance) for three major cities in the UAE (United Arab Emirates), namely Abu Dhabi, Dubai and Al-Ain. City data are then used to develop a comprehensive global GHI model for other nearby locations in the UAE. The ANN models use MLP (Multi-Layer Perceptron) and RBF (Radial Basis Function) techniques with comprehensive training algorithms, architectures, and different combinations of inputs. The UAE models are tested and validated against individual city models and data available from the UAE Solar Atlas with good agreement as attested by the computed statistical error parameters.

The optimal ANN model is MLP-based and requires four mean daily weather parameters; namely, maximum temperature, wind speed, sunshine hours, and relative humidity. The computed statistical error parameters for the optimal MLP-ANN model in relation to the measured three-cities mean data (referred to as UAE data) are MBE (mean bias error) = −0.0003 kWh/m^2, RMSE = 0.179 kWh/m^2, R^2 = 99%, NSE (Nash-Sutcliffe model Efficiency coefficient) = 99%, and t-statistic = 0.005 at 5% significance level. Results prove the suitability of the ANN models for estimating the monthly mean daily GHI in different locations of the UAE.

1. Introduction

The United Arab Emirates (UAE) is a federation of seven Emirates, namely, Abu Dhabi, Dubai, Sharjah, Umm al-Quwain, Ajman, Ras Al-Khaimah, and Fujairah, which spans approximately 83,600 square kilometers. The UAE lies in Southwest Asia between latitudes 22.0° and 26.5° N and between longitude 51° and 56.5° E. It has an arid climate that is subject to ocean effects due to its proximity to the Arabian Gulf and the Gulf of Oman. Two main seasons characterize the UAE climate, namely, the mild and warm seasons. The mild season (winter) extends from November through March, a period when temperatures seldom drop below 6 °C. The warm season (summer) stretches from April through October, with temperatures rising to about 48 °C in coastal cities, and with accompanying humidity levels reaching as high as 90%. In the southern desert areas, temperatures can climb to 50 °C [1].

Due to the high economic and demographic growth rates in the UAE, the consumption of energy kept increasing, making this country the second highest energy consumer compared to other members of the OAPEC (Organization of Arab Petroleum Exporting Countries). The UAE's per capita CO_2 emissions exceed the emissions by other Middle East countries and are only preceded by Qatar and Bahrain [2].

According to Richard Jones, deputy executive director of the International Energy Agency, the UAE will double renewable energy use by the year 2020 [3]. The UAE is taking serious steps to emerge into the solar energy market by launching the outstanding Masdar initiative in Abu Dhabi. Moreover, the UAE is the permanent host of the IRENA (International Renewable Energy Agency) headquarters. Due to its location, UAE is among the Arabian Gulf countries with very high potential for solar energy.

For the design of solar energy systems in a given area, it is critical to have accurate and detailed long-term knowledge of the available GHI (global horizontal irradiance). Apparently, the best way to acquire such data is through the installation of radiation monitoring sensors (Pyranometers) at many locations in a particular region, and which require regular maintenance and recording. The unavailability of a vast network of radiation monitoring stations encourages the development of solar radiation models.

* Corresponding author. UAE University, Department of Electrical Engineering, PO Box 15551, Al Ain, United Arab Emirates. Tel.: +971 50 6933720; fax: +971 3 7134904.

E-mail addresses: hhejase@uaeu.ac.ae (H.A.N. Hejase), maitha.h.alshamisi@gmail.com (M.H. Al-Shamisi), ali.assi@liu.edu.lb (A.H. Assi).

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This paper extends previous work by authors on individual UAE cities to develop ANN models that are capable of estimating GHI at different locations of the UAE. These models use ground-based weather data from the Abu Dhabi's NCMS (National Center of Meteorology and Seismology). The data include the maximum temperature (°C), mean wind speed (knots), sunshine (hours), mean relative humidity (%) and global horizontal irradiance (kWh/m^2). The UAE modeling data represents the average of the nine-year (2002–2008) daily mean data of three UAE cities (Abu Dhabi, Al-Ain and Dubai), and the 2009–2010 data for testing and validation. The UAE models are validated using web-based data, as well as available data for UAE cities.

2. Related work

Since the beginning of the 1990's, ANN (Artificial Neural network) techniques have been used extensively for modeling weather parameters. The proposed approaches consider different perspectives such as the number of inputs, learning algorithms, architectures, and network types. The published research work on GHI modeling spans five groups based on the primary objective of the models and output parameters. The first four groups include, respectively, the estimation of hourly, daily mean, monthly mean daily, and maximum solar radiation. The fifth group outlines the developed modeling studies to estimate solar radiation in regions where no direct measurements are available.

2.1. Models for hourly solar radiation

Sfetsos et al. [4] estimated the hourly solar radiation using artificial intelligence-based techniques. These techniques include linear, feed-forward, recurrent Elman, radial basis neural networks, and adaptive neuro-fuzzy inference scheme. The approach was extended to develop multivariate models that use other meteorological variables as possible inputs (i.e. wind speed and direction, temperature, and pressure). The authors concluded that the feed-forward technique using Levenberg–Marquardt algorithm was the optimal tool for the prediction of hourly solar radiation.

Dorvlo et al. [5] used RBF and MLP ANN models for the clearness index in the Sultanate of Oman. In this work, three MLP neural networks with one to three hidden layers and one RBF network have been implemented. The input data includes the geographical parameters (latitude, longitude, and altitude), the sunshine duration ratio (the ratio of sunshine hours to maximum sunshine hours), and a time parameter (month of the year). The RMSE (root-mean-square-error) of their optimal MLP model is 1.35 MJ/m^2/day (4.86 kWh/m^2), while the RMSE for the optimal RBF model yields 0.83 MJ/m^2/day (2.99 kWh/m^2).

Hontoria et al. [6,7] applied the concept of atmospheric transmittance or clarity index, i.e., the quotient between the global irradiation and the extra-atmospheric irradiation, to estimate the hourly solar radiation in Spain by using a feed-forward – feedback ANN model architecture. The atmospheric transmittance included a trend component (comprising the mean) and a random component (comparing the random fluctuations about the mean). In subsequent work, they used an MLP model for the trend component as well as for building random component models. The obtained results demonstrate that the developed models outperform those obtained by classical methods.

Krishnaiah et al. [8] used MLP ANN methods for estimating the hourly GHI in India. The input parameters to the neural network model included the latitude, longitude, altitude, month, time, wind speed, humidity, rainfall, air temperature, and ambient air quality. Their models compared favorably with other published ANN and empirical regression models.

Kassem et al. [9] employed the MLP ANN method to estimate the hourly total and diffuse solar radiation on a horizontal surface. The input parameters included the month of the year (January–December), time of the day (6 a.m.–5 p.m.), day of the month, ambient temperature, relative humidity, wind speed, wind direction, and mean sunshine duration per hour. The resulting statistical errors (i.e. RMSE, MBE (mean bias error) and R^2) of the hourly total solar radiation yielded 4.284 W/m^2, −0.600 W/m^2, and 93%, respectively, while those for the hourly diffuse solar radiation were 2.450 W/m^2, −3.449 W/m^2, and 78%, respectively.

2.2. Models for daily solar radiation

Elizondo et al. [10] employed the back-propagation ANN method to estimate daily radiation in the southeastern USA. The authors used two types of data for their model, namely, the observed weather variables (i.e. maximum and minimum air temperatures and daily precipitation amount) and the calculated environmental variables (i.e. day length and daily total clear sky radiation). The ANN model yielded reasonably good estimation of daily solar radiation when compared with measured data, with R^2 as high as 74% and the RMSE as low as 22.92 MJ/m^2 (10.51 kWh/m^2).

Tymvios et al. [11] performed a comparative study between Angström's and ANN modeling techniques for the estimation of GHI in Athalassa, Cyprus. The ANN models used different combinations of daily values of measured sunshine duration, theoretical sunshine duration, maximum temperature and the month number. The back-propagation ANN methods employed a tangent sigmoid transfer function, two-hidden layers, and between 23 and 46 neurons. The MBE and RMSE for the best performing ANN model were 0.12% and 5.67%, respectively. The authors concluded that the ANN modeling techniques constituted a promising alternative to the traditional approach for GHI estimation, especially, in cases where radiation measurements are not readily available.

Lam et al. [12] developed MLP ANN models to compute the daily GHI in nine major thermal climatic zones and sub-zones of China, using climatic variables (i.e. normalized sunshine duration and mean temperature) and geographical data (i.e. day index, latitude, altitude and longitude). Models for the different climate regions across China showed reasonable performance with R^2 of 82% or higher.

Mubiru [13] used ANN methods to estimate the monthly mean diffuse horizontal irradiance on a horizontal surface for locations in Uganda. Weather station data included the sunshine duration, maximum temperature, cloud cover, and the geographical parameters of latitude, longitude, and altitude. The estimated GHI data were in good agreement with measured values, yielding RMSE, MBE and R^2 values of 0.385 kWh/m^2, 0.059 kWh/m^2, and 97.4%, respectively. The ANN models showed superiority over their empirical counterparts. Furthermore, Mubiru gave an extensive review of work done on the estimation of GHI using ANN techniques.

Rehman and Mohandes [14] used ANN methods to estimate the daily GHI for Abha city, Saudi Arabia (SA). The authors employed three combinations of data (i.e. the day of the year, mean and maximum air temperature and relative humidity). In addition to the day of the year, the first, second, and third models used maximum temperature, mean temperature, and mean temperature and relative humidity, respectively. The resulting MAPE (mean absolute percentage error) values for the three models yielded 4.49%, 11.8% and 10.3%, respectively. The authors concluded that not all neural network techniques were suitable for estimating GHI from the knowledge of temperature and relative humidity.

Behrang et al. [15] applied different MLP and RBF ANN methods to predict the daily GHI in Dezful city, Iran. The authors used six different combinations of the daily input data that included the day of the year, mean air temperature, relative humidity, sunshine