Energy xxx (2015) 1–10

Contents lists available at ScienceDirect

Energy

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

Prediction of monthly average global solar radiation based on statistical distribution of clearness index

T.R. Ayodele*, [1], A.S.O. Ogunjuyigbe [1]

Power Energy Machine and Drive (PEMD) Research Group, Electrical and Electronic Engineering, Faculty of Technology, University of Ibadan, Nigeria

ARTICLE INFO

Article history:
Received 30 October 2014
Received in revised form
7 June 2015
Accepted 29 June 2015
Available online xxx

Keywords:
Statistical distribution
Clearness index
Extraterrestrial radiation
Global solar radiation
Prediction

ABSTRACT

In this paper, probability distribution of clearness index is proposed for the prediction of global solar radiation. First, the clearness index is obtained from the past data of global solar radiation, then, the parameters of the appropriate distribution that best fit the clearness index are determined. The global solar radiation is thereafter predicted from the clearness index using inverse transformation of the cumulative distribution function. To validate the proposed method, eight years global solar radiation data (2000–2007) of Ibadan, Nigeria are used to determine the parameters of appropriate probability distribution for clearness index. The calculated parameters are then used to predict the future monthly average global solar radiation for the following year (2008). The predicted values are compared with the measured values using four statistical tests: the Root Mean Square Error (RMSE), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error) and the coefficient of determination (R^2). The proposed method is also compared to the existing regression models. The results show that logistic distribution provides the best fit for clearness index of Ibadan and the proposed method is effective in predicting the monthly average global solar radiation with overall RMSE of 0.383 MJ/m^2/day, MAE of 0.295 MJ/m^2/day, MAPE of 2% and R^2 of 0.967.

1. Introduction

The design, sizing and performance of any solar power project such as stand-alone photovoltaic systems, flat-plate collectors and the storage capacity of solar installation system require an accurate knowledge of available solar irradiance at the location of installation [1]. However, solar irradiance is unpredictable as it varies with space and time as a result of irregular presence of cloud [2]. Clearness index is one of the factors which can be used to evaluate the effects of cloud on extraterrestrial radiation. It is a stochastic quantity which varies with time of the day and season of the year. It can, therefore, be taken as a random variable whose future can be predicted within a specific range through a statistical analysis of its past occurrence [3]. The solar radiation on the horizontal surface can be estimated by determining the clearness index which is the sky condition of any given site [4].

For any solar power project to be successful, long-term solar radiation data are required [5] and this may not be available especially in developing countries due to the high cost of measuring equipment and lack of technical capability for calibrating the measuring equipment and for interpretation. Moreover, in locations where solar radiation data are captured, the data are only available for a few months due to incessant breakdown of measuring equipment as a result of poor maintenance and high cost of replacement. Hence, generating synthetic solar radiation data seems to be the only viable practical alternative of obtaining needed data [6]. This paper contributes in this direction by proposing a method which allows solar radiation to be estimated for any given period once the probability distribution of clearness index is determined from the past available global solar radiation data.

The use of probability function in modeling clearness index was first proposed by Liu and Jordan [7] where a generalized family of distribution functions was determined for clearness index. It was concluded that these functions were independent of the geographical location and the month under consideration. Subsequently, several authors came up with different studies to determine the applicability of this claim and it was found that the claim was not universal as initially proffered. Since then, different probability densities based on the local condition have been proposed

* Corresponding author. Tel.: +234 8064339270.
E-mail address: tayodele2001@yahoo.com (T.R. Ayodele).
[1] Power, Energy, Machines and Drives (PEMD) Research Group.

http://dx.doi.org/10.1016/j.energy.2015.06.137
0360-5442/

Nomenclature

Q	measured global solar irradiation, $M\,Jm^{-2}\,day^{-1}$
Q_o	extraterrestrial solar radiation, $M\,Jm^{-2}\,day^{-1}$
I_{SC}	solar constant, Wm^{-2}
ω_s	mean sunrise hour angle, degree (°)
S	average daily sunshine hour, *hr*
S_o	maximum possible average daily length of sunshine hours, *hr*
n	Julian day number
K_T	clearness index
s	logistic distribution scale parameter
$E(.)$	expectation of daily average time series data
$var(.)$	variance of daily average time series data
X	random variable
$F(K_T)$	cumulative distribution function of clearness index
$f(K_T)$	probabilistic distribution function of clearness index
K_{TP}	predicted clearness index
R^2	coefficient of determination
$U(0,1)$	standard uniform distribution
ΔT	difference between maximum and minimum temperature, (°C)
a, b, c, d, e, f	derived regression constant for the different models
Q_p	predicted monthly average global solar radiation, $M\,Jm^{-2}\,day^{-1}$
$Q_{p(i)}$	i^{th} predicted daily average time series global solar radiation, $M\,Jm^{-2}\,day^{-1}$
$Q(i)$	i^{th} measured time series global solar radiation, $M\,Jm^{-2}\,day^{-1}$
m	number of observed global solar radiation
z	number of data of clearness index under consideration
φ	latitude of the site, degree (°)
δ	sun declination angle, degree (°)
ψ	logistic distribution location parameter, $M\,Jm^{-2}\,day^{-1}$

Abbreviations

RMSE	Root Mean Square Error, $M\,Jm^{-2}\,day^{-1}$
MAE	Mean Absolute Error, $M\,Jm^{-2}\,day^{-1}$
CDF	Cumulative Distribution Function
PDF	Probability Distribution Function
MAPE	Mean Absolute Percentage Error, %

for clearness index by different authors. Holland and Huget [3] used the classical probability theory to derive expression for the expected value of irradiance on inclined surface using the combination of clearness index and the diffused fraction of insolation. The CDC (Cumulative Distribution Curve) of clearness index of Ilorin, South West Nigeria was determined in Ref. [4]. The author concluded that the generalized CDC proposed by Liu and Jordan were not applicable to the city. Jurado et al. studied the probability distribution density of clearness index of Southern Spain using 5 min average data [8]. They observed that the mixture of two normal distributions provided a good fit for the data. Beta probability distribution function was utilised to model the clearness index, sunshine hour and the solar radiation using the data recorded at thirty-three meteorological stations in Algeria over a period of eleven years [9]. Further readings on probabilistic distribution of clearness index abound [10].

The prediction of monthly average global solar radiation using different empirical regression models has been discussed in the literature: Six new diffuse solar radiation models based on statistical regression technique were established for the city of Isfahan, Iran in Ref. [11]. The accuracy of the new model was compared with the existing models and found to be more accurate. The overall best of the models was the third degree model obtained from a function of relative sunshine hour. Muzathik et al. [12] were concerned with the development of a new exponential regression model for determining monthly average global solar radiation on horizontal surface based on Kadir Bakirci model. The authors also developed a model that is capable of converting the horizontal global solar radiation to that of a radiation on a tilted surface. Comparison of different empirical models for modelling diffuse solar radiation on horizontal surface of Turkey has also been performed [13]. It was established therein that the best model is the 3rd-order polynomial model based on sunshine duration and clearness index. The use of artificial intelligent methods in the prediction of global solar radiation has also been established in the literature: An ANN (Artificial Neural Network) based method was proposed in Ref. [14] to predict diffuse fraction of solar radiation of Egypt. The authors compared the result of the ANN model to that of the conventional regression models and concluded that ANN was more suitable for diffuse solar radiation prediction in the plains of Egypt. Yadav and Chandel [15] revealed that the prediction accuracy of ANN models depended on input parameter combinations, training algorithm and the architecture configuration.

In the same manner, Bayesian framework for ANN named as ARD (Automatic Relevance Determination) method was developed by Lopez et al. [16] for determining the relative relevance of climatological data for estimating hourly direct solar radiation. The methodology was thought to be useful in the selection of optimum input parameters into ANN models. In the work of Linares-Rodriguez et al. [17], a combination of GA (Genetic Algorithm) and ANN was developed to form an ensemble model for the estimation of global solar radiation over a large area. The model used clear sky estimates and satellite image as the input variable; it was showed that the model was an improvement over models based on satellite imagery.

Additional methods for predicting the global solar radiation have also been proposed: Hourly solar irradiance has been predicted in Ref. [18] using hybrid model based on SOM (Self-Organizing Maps), SVR (Support Vector Regression) and PSO (Particle Swarm Optimization). In their work, SOM was used to solve the noise and stationarity problem. It was reported that the hybrid method performs favorably with the traditional models. The performance of an hybrid CRO–ELM (Coral Reefs Optimization – Extreme Learning Machine) algorithm in the prediction of global solar radiation has been presented by Salcedo-Sanz et al. [19]. ELM was used to solve the prediction problem while the CRO evolves the weights of the neural network, in order to improve the solutions obtained. The CRO–ELM approach was able to accurately predict the daily global radiation better than the classical ELM, and the Support Vector Regression algorithm only.

Yang et al. [20] combined ETS (Exponential Smoothing) with the knowledge-based heuristic time series decomposition methods to improve the accuracy and computational efficiency in forecasting global solar irradiation. Three decomposition methods were proposed: seasonal-trend decomposition procedure based on LOESS (LOcally-wEighted Scatter plot Smoothing), Decomposition using the closure equation and Decomposition using cloud cover. The result reveals that decomposition using cloud cover performed best