



Stochastic generation of synthetic minutely irradiance time series derived from mean hourly weather observation data

J.M. Bright ^{a,*}, C.J. Smith ^{a,1}, P.G. Taylor ^{a,b,c}, R. Crook ^a

^a School of Chemical and Process Engineering, Energy Research Institute, University of Leeds, Leeds LS2 9JT, UK

^b School of Earth and Environment, Sustainability Research Institute, University of Leeds, Leeds LS2 9JT, UK

^c Centre for Integrated Energy Research, University of Leeds, Leeds LS2 9JT, UK

Received 22 September 2014; received in revised form 20 February 2015; accepted 21 February 2015

Communicated by: Associate Editor Jan Kleissl

Abstract

Synthetic minutely irradiance time series are utilised in non-spatial solar energy system research simulations. It is necessary that they accurately capture irradiance fluctuations and variability inherent in the solar resource. This article describes a methodology to generate a synthetic minutely irradiance time series from widely available hourly weather observation data. The weather observation data are used to produce a set of Markov chains taking into account seasonal, diurnal, and pressure influences on transition probabilities of cloud cover. Cloud dynamics are based on a power-law probability distribution, from which cloud length and duration are derived. Atmospheric transmission losses are simulated with minutely variability, using atmospheric profiles from meteorological reanalysis data and cloud attenuation derived real-world observations. Both direct and diffuse irradiance are calculated, from which total irradiance is determined on an arbitrary plane. The method is applied to the city of Leeds, UK, and validated using independent hourly radiation measurements from the same site. Variability and ramp rate are validated using 1-min resolution irradiance data from the town of Cambourne, Cornwall, UK. The hourly irradiance frequency distribution correlates with $R^2 = 0.996$ whilst the mean hourly irradiance correlates with $R^2 = 0.971$, the daily variability indices cumulative probability distribution function (CDF), 1-min irradiance ramp rate CDF and 1-min irradiance frequency CDF are also shown to correlate with $R^2 = 0.9903$, 1.000, and 0.9994 respectively. Kolmogorov–Smirnov tests on 1-min data for each day show that the ramp rate frequency of occurrence is captured with a high significance level of 99.99%, whilst the irradiance frequency distribution and minutely variability indices are captured at significances of 99% and 97.5% respectively. The use of multiple Markov chains and detailed consideration of the atmospheric losses are shown to be essential elements for the generation of realistic minutely irradiance time series over a typical meteorological year. A freely downloadable example of the model is made available and may be configured to the particular requirements of users or incorporated into other models.

© 2015 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Keywords: Irradiance generation; Resource modelling; Minute resolution; Stochastic modelling; Cloud cover

1. Introduction

Solar irradiance varies on a minutely time scale (Sayeef et al., 2012). The fluctuations are driven by cloud dynamics, atmospheric losses (Calinoiu et al., 2014), and the transport of airborne pollutants (Vindel and Polo, 2014a). Changes in irradiance that occur on the same time

* Corresponding author.

E-mail addresses: pm08jmb@leeds.ac.uk (J.M. Bright), pmcjs@leeds.ac.uk (C.J. Smith), P.G.Taylor@leeds.ac.uk (P.G. Taylor), R.Crook@leeds.ac.uk (R. Crook).

¹ Address: UK Network of Energy Centres for Doctoral Training, University of Leeds, UK.

Nomenclature

Latin alphabet

C	cloud coverage fraction ($C/10$)
C_8	cloud coverage in okta (0–8)
epm	elements per minute in matrix
f	white-noise multiplier for k_c variations
G	irradiance, specified by subscript (W m^{-2})
i	random start point within row vector
k_c	clear-sky index (G/G_{cs})
n	number of elements within a re-sampled cloud length row vector
\mathbf{P}^1	transition probability matrix
$P(x)$	probability of x to occur
r	random variable between 0 and 1
R	resolution of primary \mathbf{x} (100 m/el)
s	number of states in Markov process
t	time-step in Markov process
u	wind speed (ms^{-1})
u_{10}	u measured 10 m above ground (ms^{-1})
x	horizontal cloud length (m)
X	state at point t in Markov process
\mathbf{x}	cloud cover row vector of 1's and 0's
\mathbf{x}_ψ	cloud cover row vector adjusted by ψ
z	cloud height (m)
$z_{0\text{ref}}$	roughness length (m)

Numerical

0	used to represent clear sky minute
1	used to represent a clouded minute
60	used as a conversion for secs to min

Greek alphabet

α	coefficient defined by x_{max}
β	single power law exponent
β	tilt angle from horizontal of inclined plane
δ	coefficient defined by x_{min}
ϵ	minutely fluctuation from k_c
θ_i	solar incidence angle normal to angled plane
θ_z	solar zenith angle
σ	std. dev. around hourly mean of k_c
ψ	sampling rate

Subscript

\mathbf{B}	beam (direct)
\mathbf{B}	denoting a Boolean matrix
clear	clear minute
cloud	cloudy minute
cs	clear sky
C	denoting cumulative probability in matrix
D	diffuse
i	the i th state at time $t - 1$
j	the j th state at time t
m	minutely
max	maximum value
min	minimum value
n	the n th order of a Markov process
P	panel (arbitrary alignment)
ref	value at a reference measurement
s	number of states in Markov process

scale as changes in electricity demand will impact the benefits of storage and self-consumption in a domestic or community PV system (Marcos et al., 2014). Integrated electricity demand, PV supply, and storage simulations must operate on a minutely time scale to capture these effects, and therefore require minutely irradiance time series as an input (Widen et al., 2015; Sayeef et al., 2012; Hummon et al., 2012; Cao and Sirén, 2014). Calibrated minutely irradiance datasets are generally the output of isolated research projects and are often limited in duration, measurement consistency, and location. Hourly weather data, however, is widely collected and made available through national meteorological offices. This hourly data fails to capture the intermittent nature of solar irradiance (Sayeef et al., 2012), therefore some solar irradiance models use hourly weather datasets to artificially generate minutely irradiance time series.

The focus of solar irradiance models can vary from predicting the future irradiance, to providing a general expected irradiance at any location globally. Many examples of these models have been reviewed, analysed and validated in

literature (Gueymard, 2012). The methodology of interest is a sun obscured type approach. This is where the cloud cover is predicted or determined, thereby implying when the solar beam irradiance will be obstructed. A more complex methodology is outlined and developed by Morf (1998, 2011, 2013) where cloud cover is two-dimensionally modelled to replicate sky with certain clouded conditions, whilst a random number generator driven model separates irradiance into its subcomponents of diffuse and beam. Atmospheric transmission losses from extraterrestrial irradiance to global horizontal irradiance is extensively detailed in literature, however its inclusion on a time series irradiance generation model is less so. Simplistically, clouded periods can be subjected to a random variate to represent these losses (Ehnberg and Bollen, 2005), however there is scope for a more sophisticated approach. Geographically dependent monthly clearness index distributions can be used to deterministically select the transmission losses during clouded periods (Morf, 2013). Probabilistic methods are commonly seen to generate irradiance data by stochastically selecting the clearness index

Download English Version:

<https://daneshyari.com/en/article/7937952>

Download Persian Version:

<https://daneshyari.com/article/7937952>

[Daneshyari.com](https://daneshyari.com)