Available online at www.sciencedirect.com

ScienceDirect

Solar Energy 110 (2014) 615–626

SOLAR ENERGY

www.elsevier.com/locate/solener

Sunshine and cloud cover prediction based on Markov processes

Heinrich Morf *

Buechraiweg 47, 5452 Oberrohrdorf, Switzerland

Received 28 March 2014; received in revised form 29 May 2014; accepted 30 September 2014

Communicated by: Associate Editor Christian Gueymard

Abstract

A novel prediction method for sunshine and cloud cover is presented that minimizes the root mean square error of the predictions. It bases on a homogeneous recurrent Markov process with discrete states. The outstanding feature of the method is that the exact value of the prediction error is a priori known, prior to making any prediction. Within the limits of the underlying model to mimic the real world, it is an estimate for the best possible result of sunshine and cloud cover predictions. It is found that the best prediction alters from persistence over a short time horizon to the expectation of the steady state vector of the Markov process over a long prediction horizon, whereby the root mean square error changes from 0 to the standard deviation of the steady state vector. The prediction method was applied to two simple solar irradiance models under the assumption that the prediction errors are only caused by the stochastic behavior of sunshine and cloud cover. The calculated prediction errors were found to be in qualitative agreement with those reached in the real world.

Keywords: Cloud cover; Forecasting; Solar irradiance; Sunshine

1. Introduction

The past few years have witnessed great efforts to better forecast solar irradiance. Over short prediction horizons (seconds, minutes, sometimes hours) the driving force was the promise of improvements in operation and control of solar energy harvesting systems. Over longer prediction horizons (rarely minutes, hours, days), the research was mainly driven by the need to keep the electrical utility grid stable, and to operate it in a cost-effective manner, even when there was a high contribution of photo voltaic solar energy to the generating capacity.

In the year 2013 many researchers have reported about recently developed prediction methods and their performance:

(1) Chu et al. (2013) report on direct normal irradiance forecasts with sky image processing and stochastic learning. They predict 1-min-averages over time horizons of 5 and 10 min for Merced, California.
(2) Fu and Cheng (2013) predict global irradiance on a horizontal plane with all-sky image features via regression. They compare the results of 5, 10, and 15 min predictions in Taiwan with 1-min-averages of 10-s-ground-truth data.
(3) Huang et al. (2013) present the use of their Coupled AutoRegressive and Dynamical System (CARDS) model for the prediction of the hour-by-hour sequence of hourly means of global irradiance on a horizontal plane in Mildura, Australia for the year 2000.
(4) Lonji et al. (2013) make power production forecasts for a photovoltaic fleet dispersed over an area of 50 km by 50 km in the Tucson, Arizona region over time horizons from 15 min to 90 min by use the fleet's single unit output power measurements.

* Tel.: +41 56 496 81 20.
E-mail address: heinrich.morf@bluewin.ch

http://dx.doi.org/10.1016/j.solener.2014.09.044
0038-092X/

Nomenclature

Capital Letters

A	sky area (m^2)
F	distribution function
G	global irradiance on a horizontal plane ($W\ m^{-2}$) without index it refers to the global irradiance on the ground
H	daily irradiation on a horizontal plane ($J\ m^{-2}\ d^{-1}$) without index it refers to global irradiance on the ground
K	daily clearness index ($=H/H_0$) (–)
MSE	mean square error (the square of $RMSE$)
$nRMSE$	normalized root mean square error (the $RMSE$ normalized to the mean of the measurements)
N	generic counter limit
P	probability (–)
$RMSE$	root mean square error (the square root of MSE)
SIF	stochastic insolation function (–)
T	time in the sense of duration (s)
X	generic random variable
W	steady state probability (–)

Small Letters

a	generic constant
b	generic constant
b	slope of the Ångström–Prescott regression (–)
cc	cloud cover (–)
f	probability function, probability density function
k^*	instantaneous clear sky index ($= G/\overline{G_o}$) (–)
pdf	probability density function
t	time (s)
vv	vertical visibility (–)
x	outcome of a trial with X.

Greek Letters

μ	expectation, mean
σ	standard deviation
σ^2	variance
τ	time span (s)
$\bar{\tau}$	transmission factor for global irradiance passing through clouds (–)

Special Characters

$\bar{}$	expectation, mean
^	prediction
*	with reference to the clear sky
[...]	matrix

Indices

0	where the view to the sun is obstructed by clouds ($SIF(t)$, $vv\ (t)$)
0	part of the sky that is cloud free (A, $cc(t)$)
1	where the view to the sun is clear ($SIF(t)$, $vv(t)$)
1	part of the sky that is covered by clouds (A, $cc(t)$)
b	beam
d	diffuse
h	hour of the day
i	row
j	column
o	above clouds
obs	observed
s	sunshine

(5) Perez et al. (2013) analyze the performance of forecasts based on numerical weather prediction models (NWP models) for sequences of hourly means of global irradiance on a horizontal plane over time horizons of 1, 2, and 3 days in the USA, Canada, Central Europe, and Southern Spain.
(6) Ronzio et al. (2013) present a survey on radiative and cloud schemes for solar irradiation modeling. They use their findings for the prediction of sequences of hourly means of global irradiance on a horizontal plane over 1, 2, and 3 days at three Italian sites located in Milano (Northern Italy), Casaccia (Central Italy), and Catania (Southern Italy).
(7) For a summary of the present state of the art of solar irradiation forecasting see Pelland et al. (2013).

What drew our attention is the rather low accuracy of the predictions reported by all authors; normalized root mean square errors in the order of tens of percentage points are common. Thus, we began to wonder whether some insuperable constraints were inhibiting better results. We quickly came to the conclusion that it is the stochastic component of solar irradiance that impedes a precise prediction. Think of the prediction of the outcome of the throw of a dye: five out of six predictions will be wrong. The point to stress is that there is no way to improve this result. In this paper we set out to fathom the limits of solar irradiance predictions. We do so by analyzing the stochastic behavior of sunshine and cloud cover, which are the prime drivers of the stochastic behavior of solar irradiance. The results are then used to estimate the minimum possible prediction errors on solar irradiance.

Developments of random number generator driven solar irradiance models have led to a better understanding of the cloud related stochastic component of solar irradiance (see Morf, 1998, 2011, 2013, 2014). This knowledge allowed to develop the prediction methods for sunshine and cloud cover presented in this paper, which build on homogeneous