Solar Energy 159 (2018) 852–867

Contents lists available at ScienceDirect

Solar Energy

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

Intra-hour direct normal irradiance forecasting through adaptive clear-sky modelling and cloud tracking

Viv Bone*, John Pidgeon, Michael Kearney, Ananthanarayanan Veeraragavan

School of Mechanical and Mining Engineering, The University of Queensland, Brisbane, Queensland 4067, Australia

ARTICLE INFO

Keywords:
DNI forecasting
Cloud tracking
Concentrating solar power
Cloud motion vector

ABSTRACT

Hybrid fossil-solar power cycles possess high solar-to-electric conversion efficiency and the potential to provide stable power output without the need for costly storage systems. However, the power output of the concentrating solar power (CSP) component of the plant can fluctuate in sync with intermittent direct normal irradiance (DNI). For hybrid plants, the controllable fossil-fuel unit can be used to compensate for shortfalls in CSP output during periods of light DNI intermittency or provide the entire plant output during periods of high DNI intermittency. This fossil-fuel unit requires 5–10 min to ramp its power output up or down to perform these balancing functions. Thus, by accurately predicting future DNI, and hence CSP output, the fossil-fuel unit can guarantee stable plant-wide power output during periods of intermittency.

This paper develops an intra-hour DNI prediction system using a ground-based cloud motion vector (CMV) framework and real-time DNI measurements. This system comprises a clear-sky DNI model and a cloud fraction prediction algorithm. The presented CSM is based on the Ineichen model (Ineichen, 2008), where the model parameters are adaptively estimated from identified clear-sky DNI measurements over a moving window. For the cloud fraction prediction model, this paper presents an enhanced "sector-ladder" method (Quesada-Ruiz et al., 2014) that uses the weighted mean of circular quantities (Fisher, 1995) and autoregressive filtering to improve cloud flow predictions. Furthermore, a method to forewarn against periods of high DNI intermittency using the generated DNI predictions is presented.

The proposed DNI prediction system is evaluated using 37 days of sky-camera images and DNI data collected over the summer of 2014/2015 at the University of Queensland. Over all test days, the adaptive CSM has an average root mean square error of 3.06%, which represents a 19% improvement over a CSM that uses the optimal model parameters from the previous day's data. Additionally, the modifications to the cloud flow prediction algorithm (the sector-ladder method) are shown to improve the cloud velocity prediction accuracy by a factor of seven over a period of visually determined constant cloud velocity. We find the overall prediction accuracy of the DNI prediction system to be statistically similar to the accepted short-term benchmark of persistence; however, it performs more consistently over a range of weather conditions and is able to forewarn against periods of impending intermittency with 93% accuracy. The latency from data collection to prediction is less than 30 s, making the method eminently suitable for real-time applications.

1. Introduction

Hybrid fossil-solar power cycles, such as the integrated solar combined cycle (ISCC), have the potential to provide stable power output without the need for costly storage systems (Montes et al., 2011; Rovira et al., 2013). These cycles consist of a concentrating solar power (CSP) component and a fossil-fuel component, whose power outputs are combined before being distributed to the electricity grid. The controllable fossil-fuel component can be used to maintain a stable total power output during periods of fluctuating CSP output caused by intermittent solar irradiance. This component can compensate for the shortfall in CSP output during periods of low intermittency or provide the entire hybrid cycle output during periods of high intermittency. However, typical fossil-fuel components, such as the gas turbine used in the ISCC (Montes et al., 2011), require 5–10 min to ramp power output up or down. Thus, to enable the fossil-fuel component to perform this balancing function, accurate CSP output predictions on the same timescale are required.

CSP output is driven by the direct normal irradiance (DNI) received at its collectors. Hence, accurate CSP output predictions require a

* Corresponding author.
E-mail address: viv.bone@uqconnect.edu.au (V. Bone).

https://doi.org/10.1016/j.solener.2017.10.037
Received 10 July 2017; Received in revised form 4 October 2017; Accepted 9 October 2017

thermodynamic plant model that relates DNI input to power output, and the DNI predictions themselves. This paper focuses on the prediction of DNI over horizons sufficient to predict CSP output 10 min into the future. Thus, this paper details the development of a new system that uses sky-camera images and pyrheliometer (DNI sensor) data to predict intra-hour DNI. In addition to predicting DNI, we present a method to forewarn against periods of high intermittency. During these periods, CSP output fluctuates rapidly, and thus a hybrid plant operator may wish to switch to fossil-only generation in advance to guarantee power output stability.

Many classes of DNI prediction methods exist. Each performs best (i.e. minimises prediction error) on a different timescale. Persistence methods perform best for prediction horizons of under 10 min, while ground-based cloud motion vector (CMV) methods perform best for prediction horizons of between 10 min and 1 h (Law et al., 2014; Kleissl). However, persistence methods assume that the current level of cloud cover persists for the entire prediction horizon. This simplistic assumption renders persistence methods incapable of predicting ramp events – rapid changes in DNI due to cloud motion – that are characteristic of periods of intermittency. Hence, ground-based CMV methods are the focus of this work.

Ground-based CMV DNI prediction methods comprise two separate processes, known as the ‘cloud fraction prediction process’ and the ‘clear-sky DNI prediction process’, whose outputs are combined to generate DNI predictions. The cloud fraction prediction process involves using sky imaging equipment to track cloud flow. This cloud flow information is processed using computer vision algorithms to predict future levels of sun-occluding cloud cover, expressed as a ‘cloud fraction’ (Law et al., 2014). To predict DNI, cloud fraction predictions are combined with ‘clear-sky DNI’ predictions (Law et al., 2014; Quesada-Ruiz et al., 2014; Coimbra et al., 2013) – predictions of surface level DNI for *cloudless* conditions. The complete DNI prediction process is outlined in Fig. 1. The outputs of the clear-sky DNI and cloud fraction prediction processes are combined according to

$$\widehat{B}_{t+H_p} = B^{clr}_{t+H_p}(1-C^{f}_{t+H_p}), \tag{1}$$

where B^{clr} and C^f are the outputs of the clear-sky DNI and cloud fraction prediction processes respectively, at time t for the prediction horizon H_p.

Clear-sky DNI prediction processes make use of so-called ‘clear sky models’ (CSMs) which predict clear-sky DNI at a specific time and location. CSMs predict incident DNI at a specific time and place on the Earth’s surface for cloudless conditions. Clear-sky DNI depends on extraterrestrial solar irradiance and the degree to which this irradiance is attenuated during transmission through the atmosphere (Law et al., 2014). High-fidelity CSMs such as REST2 (Reno et al.) and Solis (Mueller et al., 2004) use numerous atmospheric parameters to model this attenuation accurately. These high-fidelity CSMs, however, face a limitation in that they require an array of costly meteorological sensors to measure these parameters. This paper develops a more cost effective clear-sky DNI prediction process that requires only a single DNI sensor.

The clear-sky DNI prediction process presented here employs a simplified adaptation of the Solis model (henceforth known as the Ineichen model) (Ineichen, 2008) which uses only three atmospheric parameters and solar position as inputs. Values for these atmospheric parameters are periodically updated through an estimation process, rather than from direct measurements. This estimation process involves classifying incoming DNI measurements into ‘clear sky’ and ‘non clear sky’ data sets and then estimating values for the atmospheric parameters such that the deviation between the predicted and measured *clear sky* data sets is minimised within a moving window, similar to the approach followed in Reno et al.. The parameter estimates obtained via this estimation process are then used to predict DNI using the Ineichen model. This allows the system to adapt to changing atmospheric conditions throughout the day. We note that recent work (Engerer and Mills, 2015) has shown that the ESRA model (Rigollier et al., 2000) slightly outperforms the Ineichen model in Australia. The ESRA model is equally amenable to the estimation process detailed in this paper, and thus, the accuracy of the clear-sky DNI prediction process presented in this paper could be marginally improved by using this model.

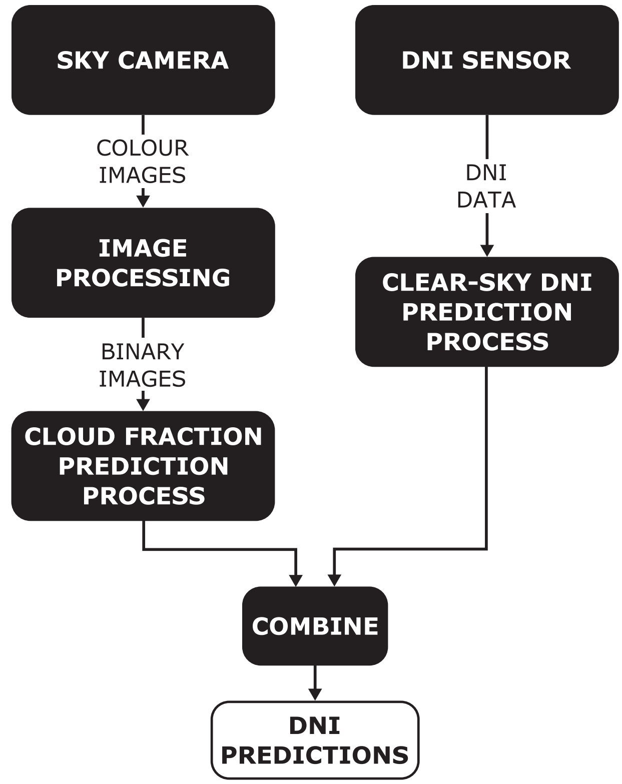

Fig. 1. Ground-based CMV DNI prediction processes combine the outputs of two separate processes, the ‘clear-sky DNI prediction process’ and the ‘cloud fraction prediction process’, to predict intra-hour DNI. The clear-sky DNI prediction process predicts DNI for *cloudless* conditions using sun position and atmospheric conditions. The cloud fraction prediction process predicts future sun-occluding cloud cover using computer vision techniques.

Cloud fraction prediction algorithms use sky imagers to track cloud motion, enabling the level of sun occluding cloud cover to be predicted (Bradbury and Fujita, 1968). Ground-based CMV methods consist of two steps: (1) the cloud decision process and (2) the cloud motion prediction process. The cloud decision process involves classifying raw sky-image pixels as clear sky or cloud and the cloud motion prediction process involves computing cloud velocity vectors over each sky image. The cloud velocity vectors obtained in step 2 are used to advect the cloud image obtained in step 1, thereby predicting future cloud cover.

Many cloud decision processes exist (West et al., 2014). Most commonly, the ratio of red image channel to blue image channel (known as the red-blue-ratio) is used to convert raw sky images into binary (cloud or clear sky) or ternary (light cloud, thick cloud, or clear sky) cloud images (Yang et al., 2014; Chow et al., 2011). Although effective, this approach requires the maintenance of a so-called ‘clear-sky library’, which contains the red-blue-ratio of all parts of the sky for clear sky conditions, and an expensive sky camera with high dynamic range and lossless compression (West et al., 2014). Alternatively, machine-learning classifiers can be used to generate cloud images from various inputs including sky image colour properties, solar azimuth and zenith, and estimated cloud movement between successive images (West et al., 2014; Bernecker et al., 2013). This approach performs well, even with inexpensive cameras, although it requires a user to manually classify sky pixels as cloud or clear sky to generate training data. In this paper, however, we use the existing EKO Instruments Findclouds software (EKO Instruments) for cloud classification and focus on the cloud