ABSTRACT

Spatio-temporal variability of solar radiation is the main variable affecting the photovoltaic power feed-in to the grid. Clouds are the main source of such variability and their velocity is a principal input to most short-term forecast models. The main goal in this study is to estimate cloud speed using radiometric data using measurements from 8 sensors located at the UC San Diego Solar Energy test bed.

Two different methods were developed to estimate the cloud speed based on the correlation between the signals received at different sensors. Our analysis showed good agreement between both methods. Additional measurements from nearby METAR and radiosonde stations also show comparable results. Both methods require high variability in the input radiation.

1. INTRODUCTION

In a high PV penetration scenario, one of the most important problems to solve is the variability of the power input to the grid. Spatio-temporal variability of solar radiation is the main variable affecting the photovoltaic power feed-in to the grid. Clouds are the main source of such variability and their velocity is a principal input to most short-term forecast models.

A common approach in the cloud motion vector estimation is to use satellite imagery (1, 2, 3). Satellite derived motion vectors have been used also to improve the results from numerical models, Velden et al (1998) showed that the GOES multispectral wind information had a significant positive impact on the numerical model derived forecasts for tropical cyclone tracks (4). Bedka and Mecikalski (2005) improved the Velden et al. (1998) algorithm to derive motion vectors including both synoptic-scale and mesoscale flows, such mesoscale flows are important in applications that monitor the rapid evolution of (convective) clouds in near real time (5).

A recent effort has been made to define the forecast horizon where the satellite based motion vector outperforms the NWP models (6, 7). In Miller et al. (2011), it is pointed out the inability of the NWP technique to obtain accurate results in the first hours of forecast due to the spin-up time required for this models (6), while Perez et al. (2010) conclude that for forecasts up to 5 hours ahead satellite-derived cloud motion-based forecasting leads to a significant improvement over NDFD forecasts. For 1 h forecasts the results from NDFD and satellite-derived cloud motion are found to be on par, probably due to satellites navigation and parallax uncertainties, which tend to mitigate for longer times (7).

This 1 hour gap of reliable cloud motion vectors for short-term forecasting could be filled by utilizing ground measurements of solar irradiance at the site of interest. The main goal in this study is to estimate cloud speed using radiometric data, with an experimental setup consisting of eight silicon pyranometers with an acquisition frequency of 20Hz, deployed in a semicircular shape at the UC San Diego Solar Energy test bed.
Two different methods were developed based on the correlation between the signals received at the different sensors. The basic premise is that for a pair of sensors aligned with the cloud direction, their irradiances will be very similar, but with a time lag. Once the lag has been determined, cloud speed can be calculated. Since cloud direction is variable several pairs of sensors covering all the possible directions have to be set up. The most correlated pair is assumed to be in the direction of the cloud motion. An alternative method is proposed using a reduced set of three sensors, which calculates the speed and direction of the clouds assuming a certain shape for the shadow edges passing through the array. Our analysis showed good agreement between both methods. Additional measurements from nearby METAR and radiosonde stations also show comparable results. Both methods require high variability in the input radiation; cloud speed of an overcast cloud layer or the atmospheric velocity in clear skies cannot be obtained.

2. DATA

In this study we have used Global Horizontal Irradiance (GHI) measured at 8 pyranometers model Li-200SZ with an acquisition frequency of 20Hz. The sensors were deployed in a semicircular shape with a radius $r$ of 6m as shown in Fig. 1, at the UCSD Solar Energy Test Bed (UCSD-SETB).

![Pyranometers distribution](image)

**Fig. 1:** Pyranometers distribution.

In addition, in the validation process we used radiosonde data from the Integrated Global Radiosonde Archive (IGRA) (8), and METAR data collected from a nearby station (Montgomery Field) extracted from the Integrated Surface Hourly (ISH) Data (9), archived at the National Climatic Data Center (NCDC). The radiosonde data include geopotential height, wind direction, and wind speed at standard, surface, tropopause, and significant levels. Table 1 shows the main characteristics of the different data sets used in this work.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>UCSD-SETB</th>
<th>IGRA</th>
<th>ISH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latitude [$^\circ$]</td>
<td>32.885</td>
<td>32.85</td>
<td>32.817</td>
</tr>
<tr>
<td>Longitude [$^\circ$]</td>
<td>-117.240</td>
<td>-117.12</td>
<td>-117.139</td>
</tr>
<tr>
<td>Altitude [m]</td>
<td>131</td>
<td>132</td>
<td>129</td>
</tr>
<tr>
<td>Frequency</td>
<td>20 s$^{-1}$</td>
<td>2 day$^{-1}$</td>
<td>1 h$^{-1}$</td>
</tr>
</tbody>
</table>

3. METHODS

Two different methods were developed to estimate the cloud speed, based on the correlation between the signals received at the different sensors.

### 3.1 Most Correlated Pair Method (MCP)

The basic premise is that for a pair of sensors $S_a$ and $S_b$ aligned with the cloud motion, separated a distance $D$, the irradiances $I_a$ and $I_b$ will be very similar, but with a time lag $t_{ab}$ as shown in Fig. 2.

Once the lag has been determined (e.g. analyzing the signal cross correlation), cloud speed can be calculated as

$$v = \frac{D}{t_{ab}}$$  \hspace{1cm} Eq. 1

MCP method uses the whole set of sensors, and is based on the simplified case depicted on Fig. 2, but without a prior assumption on the cloud direction. The 8 sensors are grouped in 7 pairs, where all the pairs share the central sensor. After calculating the cross correlation coefficients for the 7 pairs, the one with the highest correlation is assumed to be the most aligned with the cloud motion vector, and time lag and cloud speed are calculated using the most correlated pair.

![Simple case with 2 sensors](image)
The main drawback of the MCP method is the discrete nature of the results, which can be minimized by increasing the number of sensors. In this work, the selected interval was 30 degrees. This method is assumed to be the most accurate and will be used together with the measured METAR and radiosonde data for validation purposes.

3.2 Linear Cloud Edge Method (LCE)

LCE method uses the sensors labeled as $o$, $E$ and $N$ on Fig. 1, where both distances $oN$ and $oE$ are the same: $D = 6m$. The most important assumption is that the cloud edge shape can be simplified as linear when reaching the sensors array. It is also assumed that the clouds have constant speed and direction during the time taken to pass over the three sensors. Figure 3 shows the main angles and distances used in this method, where $\beta$ is the angle between the cloud edge and the $x$ axis and $v$ is the cloud speed. $\alpha$ stands for the angle between the cloud direction and the $x$ axis.

![Fig. 3: Cloud edge passing through the array.](image)

Due to the small scale of the sensor array if compared against the cloud dimensions, it is also assumed that the cloud is large enough to pass across the three sensors. Then we can calculate the time needed for the cloud to go from the sensor $N$ to $C_n$ ($t_{on}$) and from $C_e$ to $E$ ($t_{oe}$). In this case, the cloud motion direction is given by either the lines $NC_n$, $C_e E$ or the motion vector. Equations 2-12 show the steps taken to calculate the cloud speed and direction from the data.

Using the cloud speed $v$

\[
v = [v \cos \alpha, v \sin \alpha]
\]

Eq. 2

the sensors position

\[
r_o = [0,0]
\]

\[
r_N = [0,D]
\]

\[
r_E = [D,0]
\]

Eq. 3

and the edge equation at the origin

\[
y = \tan(\beta) \cdot x
\]

Eq. 4

Basic kinematic equations can be used to reach the analytic expressions for $t_{on}$ and $t_{oe}$.

\[
t_{oe} = -\frac{D \tan \beta}{v (\sin \alpha - \cos \alpha \tan \beta)}
\]

Eq. 5

\[
t_{on} = -\frac{D}{v (-\sin \alpha + \cos \alpha \tan \beta)}
\]

Eq. 6

Reducing eqs. 5 and 6 or applying the Law of sines to the triangles $oNC_n$ and $oEC_e$, an expression for $\beta$ can be easily obtained:

\[
\beta = \tan^{-1}\left(\frac{-t_{oe}}{t_{on}}\right)
\]

Eq. 7

Processing the experimental data to obtain $t_{on}$ and $t_{oe}$, will lead to three unknowns ($\beta$, $\alpha$ and $v$), and two equations 5-6. Or after replacing $\beta$ from eq. 7, there still will be two unknowns and just one equation.

\[
t_{on} \sin \alpha + t_{oe} \cos \alpha = -D/v
\]

Eq. 8

The additional information needed to solve eq. 8, can be obtained from a second cloud edge passing through the sensors, with same $v$ and $\alpha$, but with a different $\beta$ (i.e. $t_{on}$ and $t_{oe}$). Because all directions are possible for $\beta$, this second measurement should be easy to get if the assumption of constant velocity is valid for the considered interval.

Assigning the index 1 for the first pass, and 2 for the second leads to eq. 9

\[
t_{on1} \sin \alpha + t_{oe1} \cos \alpha = D/v
\]

\[
t_{on2} \sin \alpha + t_{oe2} \cos \alpha = D/v
\]

Eq. 9

that can be reduced to

\[
A \sin \alpha + B \cos \alpha = 0
\]

Eq. 10
where
\[ A = t_{on2} - t_{on1} \]
\[ B = t_{oe2} - t_{oe1} \]

Equation 11 can be solved as:
\[ \alpha = \tan^{-1}\left(-\frac{B}{A}\right) \]

Once \( \alpha \) is obtained from eq. 12, \( v \) can be calculated using eq. 9.

**4. RESULTS**

The methods were tested for the dates 10/20/2011 and 10/21/2012. Figure 4 shows the measured GHI at the central sensor \( S_o \) for the 20th of October. Radiosonde and METAR measurements were used for both days, Fig. 5 shows the two radiosonde profiles measured on October 20th for the Wind direction \( d_w \) at different geopotential heights, and the same information for the Wind speed \( s_w \). The only measurement usable to compare the results obtained in this work is the one taken at 16:23 PST, which is the closest in time to the recorded irradiation values.

METAR data can be used to determine the cloud layer height \( h \) in order to select the right altitude in the wind profile that is being measured by the ground sensors. Table 2 shows the measured \( d_w \) and \( s_w \) values at 16:23 PST that can be used in this preliminary test for the models LCE and MCP.

**TABLE 2. CLOUD SPEED AND DIRECTION MEASURED VALUES.**

<table>
<thead>
<tr>
<th>Radiosonde Date</th>
<th>METAR h [m]</th>
<th>( d_w ) [°]</th>
<th>( s_w ) [m/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oct-20-11 16:23 PST</td>
<td>487</td>
<td>140</td>
<td>3.6</td>
</tr>
<tr>
<td>Oct-21-11 16:23 PST</td>
<td>172</td>
<td>295</td>
<td>4.6</td>
</tr>
</tbody>
</table>

MCP method results shows a high dependence with GHI variability, being unable to output a stable wind direction \( d_w \) in complete overcast conditions. To illustrate this, Fig. 6 shows 20 minutes of October 21st where MCP outputs a random direction in the range \([-180, 180]\) for the first 10 minutes. In this interval both the maximum cross correlation factor and the standard deviation of GHI are low, but for the rest of the time interval \( d_w \) becomes more stable around \(-60°\) (i.e. \(300°\)).
Solar irradiation in this second interval shows larger variability and also an improved maximum cross correlation factor.

After utilizing the MCP method, a quality control process was applied to the resulting $d_w$ values to avoid poorly correlated data. The discarded data could lead to random directions as those shown in Fig. 6, and a restrictive threshold of $R^2 > 0.6$ was applied. Preliminary results showed that LCE method provided similar results to MCP but with larger standard deviations, and a threshold of 30 was used for the standard deviation of $d_w$.

Figure 7 shows the $d_w$ results obtained for October 20th. The morning time presents overcast conditions and both methods fail to extract usable information from the irradiance measurements. In the interval [13-16] PST, both methods result in similar directions, also comparable to the 16:23 PST IGRA radiosonde data.

In addition, Fig. 8 shows the obtained results for October 21st. Different intervals along the day with a lower variability in the measured GHI (due to completely overcast situations or clear sky periods) do not allow enough points to pass the quality control tests for both methods. In this second day, a very different cloud direction has been also detected with comparable results for both methods and for the radiosonde measurement.

Figures 9 and 10 show the results for the cloud speed $s_w$. This results confirm those obtained for the cloud direction, with a similar output from both MCP and LCE methods and with a same range speed obtained from the IGRA database.
5. CONCLUSIONS

This preliminary study is very encouraging and shows satisfactory results for the proposed methodologies, also LCE method could be used instead of MCP to help reduce installation and maintenance costs of the sensors array. The used days showed almost opposite cloud directions, however, they were well characterized by both MCP and LCE methodologies. Cloud speed ranges were similar for both days, and also comparable to those measured by the 16:23 PST radiosondes. High variability in the GHI input is a main factor in the usability of both methods.

Future works will try to further investigate the results under a wider variety of days. Different sensor arrays are also being investigated to optimize the number of directions covered with the minimum number of sensors. Different data acquisition frequencies and radius will also be analyzed.

6. ACKNOWLEDGMENTS

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7. REFERENCES


