ABSTRACT

We report progress towards developing methods to forecast solar-power intermittency due to clouds using analysis of digital images taken with a ground-based, sun-tracking camera. We show preliminary results of block-motion estimation analysis applied to a sequence of sky images recorded in Tucson, Arizona. In addition, we discuss statistics of ramp rates and duration of cloud-induced intermittency based on the analysis of one year of photovoltaic power output data measured at one second intervals for a 2kW system.

1. INTRODUCTION

Solar power utilization at the utility-scale is a Grand Challenge [1]. A major problem is the intermittent output of solar power plants due to passing clouds and nighttime. Intermittency limits the adoption of solar power by utility companies and industry because they require reliable, predictable power generation. Discovering new ways to compensate for intermittency will accelerate the adoption of solar power.

Several techniques exist to counter the problem of intermittency including interconnecting geographically dispersed photovoltaic (PV) systems, using dispatchable spinning reserves, energy storage, and smart grids. All these methods require accurate forecasting of PV power output for safe and efficient operation. For example, utility operators require a ten minute warning to bring spinning reserves online.

Industrial scale loads that can be dynamically controlled by a solar-aware smart grid, such as water-pumps or chillers, have a finite turn-on time, i.e., they start consuming power before they produce useful work. For this reason, the decision to turn on or off a load or source requires an accurate forecast of the timing and duration of a cloud event.

Fig. 1 Motion Vectors indicating the direction and speed of cloud motion

Previous studies have demonstrated that PV intermittency due to clouds can be forecasts using numerical weather prediction (NWP) models, analysis of satellite imagery, and the use of a
ground based total sky imager [2, 3, 7]. NWP models are capable of forecasting clouds several days ahead, however the cloud arrival time is only accurate to several hours. Analysis of cloud motion in satellite imagery performs better than NWP forecasts up to forecast horizons of 3-4 hours [2-3]. But intra-hour forecasts from satellite images is challenging because of coarse spatial resolution [3-6].

In this paper we focus on using a ground based sky camera to forecast cloud movements. Chow et al. [7] demonstrated the use of a ground based total sky imager to forecast clouds up to ten minutes ahead. In this paper we demonstrate the use of a sun-tracking camera. A tracking camera has higher resolution near the sun, compared to an all-sky imager and this high resolution is independent of time of day or season. In addition, blocking the part of the sky where the sun is located (to prevent the sun from overexposing the camera) affects only a small area in the center of the image (see Fig.1).

We begin in Section 2 with a characterization of intermittency based on one year of PV power output measurements. The sun-tracking camera set up is described in Section 3. The image analysis methods and techniques employed to forecast intermittency are described in Section 4. Section 5 includes conclusions and ideas for future work.

2. CHARACTERIZATION OF INTERMITTENCY

We measured DC power from a 2kW grid connected PV system at one second intervals during one year. Fig. 2 shows a sample of PV power output data; an irradiance forecast using a NWP is shown for comparison.

To identify the effect of clouds, we compared our measurements to a clear-sky model for the same period. We identify the impact of clouds as drops in power output of more than 20% compared to the clear-sky expectation. Fig. 3 shows a 2D histogram of the number of cloud events as a function of percentage drop in output power and the duration of the cloud event.

Fig. 2: PV power output (solid) and NWP forecast (dashed)

Fig. 3: 2D histogram of the number of cloud events binned by the magnitude as well as the duration of the drop in output. Each column has been normalized in order to highlight the correlation between duration and size of drops in power.

Fig. 4: Energy lost due to intermittency. The majority of the energy loss is due to large drops (greater than 70%) that last 1 – 6 hours.

Although the vast majority of events cause a drop in power of
20-30% and last less than a minute, the majority of energy lost is due to events that cause a drop in power of more than 80% and last 1-6 hours, see Fig. 4.

Fig. 5 shows a histogram of the inverse of the derivative of our PV power time-series. This quantity represents the time it takes to go from peak power to zero power if the derivative stays constant. The figure shows the slow variation associated with the time-of-day change in PV power output as well as the fast variations due to cloud events. Changes in power output (for a 2KW flat plate system) of 80% can happen over a time of just 5 seconds.

Fig. 5 shows a histogram of the inverse of the derivative of our PV power time-series. This quantity represents the time it takes to go from peak power to zero power if the derivative stays constant. The figure shows the slow variation associated with the time-of-day change in PV power output as well as the fast variations due to cloud events. Changes in power output (for a 2KW flat plate system) of 80% can happen over a time of just 5 seconds.

For efficient management of spinning reserves as well as new smart grid technologies, it is important to know the magnitude and duration of a cloud event before it occurs, as well as the timing and ramp rate of a cloud induced intermittency. NWP models and satellite images are insufficient to forecast intermittencies at the ten minute time scale at which most cloud events occur, therefore ground based cloud imaging methods can potentially improve new solar aware smart grids.

3. SUN TRACKING CAMERA

The camera is located at the Tucson Electric Power (TEP) Solar Test Yard. The camera is mounted on an equatorial mount such that one of its axes of rotation is parallel to the earth’s axis of rotation $V_{CN}$ (pointing towards the celestial north) as shown in Fig.6. A stepper motor rotates the camera around the axis $V_{CN}$ at a rate of approximately 360° per 24 hours to track the sun. The optical axis of the camera ($V_{CZ}$) is parallel to $V_{S}$, the vector that point towards the sun (see Fig.6).

Fig. 6: Real-world reference frame ($V_{RX}, V_{RY}, V_{RZ}$). $V_{CN}$ represents the Earth's axis of rotation, pointing towards the celestial north. $V_{S}$ points towards the sun; $\theta$ = Zenith angle (angle from the vertical) in radians and $\phi$ = Azimuth angle (eastward from the north) in radians.

The tracker has an additional motor to account for seasonal changes. The camera used is a GeoVision outdoor security camera. Movies of duration 5 minutes are recorded in MPEG-4 format at a frame rate of 1 frame/sec. Videos are recorded covering the entire day from 6 a.m. till 8 p.m. Frames are then extracted from these movies for analysis. The image resolution is $1024 \times 1280$ pixels and 8 bit/pixel gray scale.

4. FORECASTING INTERMITTENCY

4.1 Computing Motion Vectors

We employ a block based motion estimation technique to track the motion of clouds in images. This technique was originally developed for video compression algorithms to reduce temporal redundancy.

The current frame for which motion vectors are to be estimated (target) is first divided into blocks. For each block with coordinates $(x_t, y_t)$ in the target frame we determine the location in the previous frame (reference) that best matches that block as illustrated in Fig.7. The best match position $(x_r, y_r)$ is defined as the location of the maximum cross

![Diagram](https://via.placeholder.com/150)

**Fig. 7:** Block based motion estimation technique. The current frame (target) is divided into blocks. For each block, the location in the previous frame (reference) that best matches that block is determined.
correlation between the block and the reference frame. The motion vector of this block is then given by \((x_t-x_r, y_t-y_r)\).

Fig 7: a) The block for which motion vectors are to be determined is shown in green b) determining the location (shown in red) in the previous frame (reference) that best matches the green block. The red arrow in b) indicates the direction where the match is found and in a) it indicates the motion vector of the block.

Since exhaustive search algorithms for block motion estimation are highly computationally expensive, a hexagon-based search algorithm proposed by Zhu et al. [8] is used. For each motion vector, we can determine whether the path of this block will cross the sun and we can estimate the time when this will happen. The next step is to convert the motion vectors in the image (corresponding to pixel movements in the camera reference frame) to motion vectors for clouds (corresponding to velocities in the real-world reference frame). To do this we first correct for the perspective of the camera.

4.2 Perspective Correction

Because of the perspective of the images, clouds far away on the horizon have a smaller angular velocity (Fig. 8) than clouds overhead. Depending on the time of day, the optical axis of the camera points in a different direction. Hence the perspective of the images changes over time. We must correct for this perspective distortion in order to obtain accurate forecasts.

In order to compensate for the perspective distortion, we convert pixel coordinates of clouds to 3D position vectors in the real-world reference frame. To do this, we first define a camera reference frame such that \(V_{CX}\) and \(V_{CY}\) correspond to up and right in the image respectively and \(V_{CZ}\) points out of the image plane. For each pixel we then determine a vector in the camera reference frame of unit length that corresponds to the direction of the object whose image is on that pixel. For example, cloud at coordinates \((x,y)\) in an image would correspond to a vector \(\overrightarrow{V_{cloud}} = (x,y,f)/|x,y,f|\) where \(f\) is a constant determined by the imaging system (roughly equal to focal length/pixel size). Note that the super script indicates the reference frame, ‘C’ for the camera reference frame, ‘R’ for the real-world reference frame.

Next, we determine a representation of \(\overrightarrow{V_{cloud}}\) in the fixed real-world reference frame (\(\overrightarrow{V_{cloud}^R}\)). Specifically we must find a matrix \(T\) such that in the real-world frame:

\[
T \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \overrightarrow{V_{CZ}^R}
\]

\[
T \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \overrightarrow{V_{CY}^R}
\]

\[
T \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \overrightarrow{V_{CX}^R}
\]
Where \( \mathbf{V}_{CZ}^R, \mathbf{V}_{CY}^R, \) and \( \mathbf{V}_{CX}^R \) are the coordinate vectors of the camera reference frame represented in real world coordinates. These three equations can be written as

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
= \mathbf{T} =
\begin{bmatrix}
V_{CX1} & V_{CY1} & V_{CZ1} \\
V_{CX2} & V_{CY2} & V_{CZ2} \\
V_{CX3} & V_{CY3} & V_{CZ3}
\end{bmatrix}
\]

What remains is to determine representations \( V_{CX}, V_{CY}, \) and \( V_{CZ} \) in real-world coordinates.

In the real-world reference frame positive X direction (\( V_{RX} \)) points towards west, positive Y direction (\( V_{RY} \)) points towards south and the positive Z direction (\( V_{RZ} \)) points vertically up with respect to the ground (see Fig. 6).

\( \mathbf{V}_{CZ}^R \) is a known vector if we know the direction of the sun at any given instant of time. We use a solar position algorithm \([9]\) to determine the zenith and azimuth angle of the sun. Once we know the zenith and azimuth angles, \( \mathbf{V}_{CZ}^R \) can be computed as:

\[
\mathbf{V}_{CZ}^R = [-\sin \varphi \sin \theta, -\sin \theta \cos \varphi, \cos \theta]
\]

Where \( \theta = \) Zenith angle (angle from the vertical) in radians and \( \varphi = \) Azimuth angle (eastward from the north) in radians (see Fig. 6). The camera is mounted on the tracker such that \( \mathbf{V}_{CX}^R \) is perpendicular to both \( \mathbf{V}_{CZ}^R \) and \( \mathbf{V}_{CN} \), therefore \( \mathbf{V}_{CX}^R \) is given by

\[
\mathbf{V}_{CX}^R = (\mathbf{V}_{CN} \times \mathbf{V}_{CZ}^R)/|\mathbf{V}_{CN} \times \mathbf{V}_{CZ}^R|
\]

where ‘\( \times \)’ indicates cross product. \( \mathbf{V}_{CY}^R \) is perpendicular to both \( \mathbf{V}_{CX}^R \) and \( \mathbf{V}_{CZ}^R \) and is therefore given by:

\[
\mathbf{V}_{CY}^R = \mathbf{V}_{CZ}^R \times \mathbf{V}_{CX}^R
\]

The cloud vector in real-world reference frame is now given by:

\[
\mathbf{V}_{\text{cloud}}^R = \mathbf{T}^{-1} \mathbf{V}_{\text{cloud}}^R
\]

The transformation matrix \( \mathbf{T} \) is a unitary matrix corresponding to a rotation, this means \( \mathbf{V}_{\text{cloud}}^R \) still has unit length. We convert this unit length vector to a cloud position vector by multiplying by a constant such that the height of the cloud \( \mathbf{V}_{\text{cloud}}^R \) is equal to 3000 meters which we assume to be the typical cloud height. We can now make estimates of cloud velocity and forecast cloud events. We pick a typical cloud height to get motion vectors with physically intuitive values; this choice does not affect predictions. The result is shown in Fig. 8.

Fig.8: Motion vectors a) without geometric correction b) with geometric correction.
4.3 Estimating Cloud Arrival Time

Based on the cloud velocities determined in the previous section, we can determine which clouds will block the sun in the future as well as the time at which this will happen. For each image, we determined which cloud would arrive soonest and estimate the time it would take for the cloud to reach the sun. Figures 7, 8 and 9 shows forecast of arrival times as a function of time before the cloud event. The horizontal axis represents the time at which the forecast is made and the vertical axis represents the forecast time.

The ten minutes ahead forecast shown in Fig. 7 is the forecast for a broken cumulus cloud moving uniformly towards the sun without much deformation. As can be seen in Fig. 9, intermittency caused by such clouds can be forecast with an accuracy of about one minute.

However, when cloud dynamics, such as cloud formation and dissipation, come into play, forecasting using motion vector analysis becomes tougher and less accurate. Figure 10 shows such a scenario in which a part of a cloud moving towards sun splits, speeds up in the direction of sun and eventually disappears before reaching the sun. This happens twice and results in forecast errors as shown by the dotted lines. Eventually the big cloud reaches the sun causing intermittency (represented by the long red line). Predictions also become less accurate when cloud movement is not uniform, see Fig.11. Future work will address these issues.

Fig. 10: Multiple clouds are tracked. However, in this case the two of the clouds disappear before reaching the sun.

Fig. 9: Ten Minute ahead forecast. The blue dots represent the forecast and the red line represents the actual time before the cloud reaches the sun. The RMS difference between the forecast and the true values is 1.4 minutes.

Fig.11: Cloud dynamics (in this case changing of shape) can cause bad forecast.

5. DISCUSSION AND CONCLUSION

We reported a characterization of PV power intermittency for 1 year in Tucson, Arizona. Based on this characterization we conclude that most of the cloud events occur at short (ten minute) time scales where conventional cloud forecasting methods like NWP and satellite image analysis are not sufficient. We describe a method to forecast intermittency up to ten- minutes ahead using a ground based sun-tracking camera.
Under ideal circumstances (single layer cloud with no deformation, splitting, disappearance or appearance) we demonstrated that our method can make ten minutes ahead forecast that are accurate to within about 1 minute. However, a known limitation of this method is that it does not account for cloud dynamics, i.e., cloud formation and dissipation.

To address this problem we plan to use more sophisticated image analysis methods to track cloud regions instead of individual blocks. In addition, we will develop ways to determine the confidence intervals and also ways to combine the forecasts using ground based cameras with other forecasting methods (e.g. satellite images) to improve forecasts, both at the 10 minute as well as 2 hour time horizons.

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7. REFERENCES


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