ABSTRACT

A pair of sky imagers has been deployed at a 48MW photovoltaic (PV) facility in Henderson, Nevada. The sky images will be analyzed using image processing techniques developed for short term forecasting of plant power output. Cloud maps generated from the two instruments will be combined to generate a single large cloud map over the site to provide coverage of the 1.3 km² plant. Future cloud positions are determined by looking at the motion of the clouds over consecutive image pairs and a forecasted position is generated. The ground projected cloud position, a binary map showing cloud shadows with a granular resolution of 6.25 m², is forecast for 0 to 15 minutes.

The forecasts are evaluated using AC inverter power production measurements, 15 plane-of-array reference modules measuring global irradiance (GI) and five weather stations measuring GI and global horizontal irradiance. The binary map of the shadows, showing either clear or cloudy conditions, is assigned an optical depth for each condition as determined from the recent time history of observations. A probability density function of observed optical depth for each condition is constructed from the last 10 minutes of measurement and the most frequent occurrence is selected as that condition's optical depth. The optical depths are then used to compute power output for the each power measurement, as well the aggregated plant output. Power output is evaluated for a 0 to 15 minute forecast horizon.

1. INTRODUCTION

The motivation to switch to renewable power production is well documented (1), (2), and arguments have been made that solar is one of the best renewable options (3). In California alone, data provided by the California Independent System Operators (4) which manage the electric grid show that solar power constitutes 956 MW of installed nameplate capacity, and data from the California Public Utilities Commission (5) show that there is another 7940 MW scheduled to come online in the next 6 years. This represents 10% of current installed capacity, and there are many more projects pending approval. This snapshot of the use of solar power is not unique to California, so the need to have a reliable forecast of solar power production is ever increasing. This need is driven by generation scheduling requirements of grid operators, and power market bidding of producers and utilities.

Different solar power applications have differing temporal and spatial scale requirements for a power forecast. The best technology to obtain the longest time horizons is numerical weather prediction (NWP) which has a forecast horizon of several days, but the drawback is that the spatial resolution is course (approximately 100 km², model dependent), and often too course to resolve individual clouds (6). Active work is being done to reduce the resolution to smaller scales where empirical parameterizations are no longer required to properly resolve the phase of water vapor
within each cell, but the horizontal resolution is still greater than 1 km². Satellite observation technology provides higher resolution measurements of cloud cover with a horizontal resolution of close to 1 km² (7). The forecast horizon for which satellites perform better than NWP is currently stated to be 6 hours, which is good for intraday forecasting (8). Recent unpublished work may suggest satellites only provide better forecasts than NWP for up to 3 hours; however with the current state-of-the-art, satellites remain a very viable approach.

The use of sky imaging for solar power forecasting is relatively recent (9), and it fills an intra-hour forecasting gap at a high spatial and temporal resolution. The use of intra-hour generation scheduling proposed by the Federal Energy Regulatory Commission (10) will add value to short term forecasting technologies. The suggested 15 minute forecasting interval is within the 20-30 minute potential forecast horizon provided by sky imaging techniques. In this paper, we describe the preliminary results of solar power forecasting using a pair of sky imaging devices located at the 48MW Copper Mountain Solar 1 facility owned by Sempra Generation.

2. EXPERIMENTAL SETUP

2.1. Sky Imager Deployment

Two model 440A Total Sky Imagers (TSI, Yankee Environmental Systems) were set up on top of two inverter houses separated by 1.8 km. Each system has a downward pointing 24-bit camera capturing images of the sky hemisphere reflected by a spherical mirror. The usable region of the 640×480 pixel camera is 420×420 pixels, corresponding to the image circle whose light originates above a zero degree elevation angle. Images from each TSI are captured every 30 seconds in a jpg compressed format. It is not possible to change this file format for the device, and a small loss of information occurs as a result of the compression. Additional information regarding the instrument used can be found in (9).

2.2. Power and Solar Measurements

To compare the TSI forecast the power and weather monitoring data of the plant is used. The power plant provided AC power measurements at the inverter level, 5 weather stations with Kipp & Zonen CMP1120 pyranometers measuring both global horizontal irradiance (GHI) and plane-of-array (POA) global irradiance (GI), and 15 reference modules which output POA GI, all at a 1 second resolution. The solar arrays for the plant cover an area of 1.3 km². The TSI designated PCS33 is on the west end of the site, and PCS41 is on the east end (Fig. 1).

3. CLOUD DECISION AND CLOUD MOTION ALGORITHMS

To detect clouds, the red-blue-ratio (RBR) method is employed, where the red channel is divided by the blue channel, and clouds are determined using a threshold which is tuned for each instrument. Because light scattered by clouds is more spectrally uniform (11) over the detectable portion of the spectrum, the RBR is close to one. The RBR of clear sky is lower because molecular scattering has a strong wavelength dependence (11) and the blue channel reads higher than the red, giving an RBR smaller than one.

The threshold is set to give the best results across a range of cloud types determined from a manual validation process consisting of image annotation and performance evaluation. See the methods described in (9) for a complete description.

The cloud decision image is projected to a georeferenced plane at the estimated cloud height (Fig. 2), hereinafter cloudmap. To estimate cloud height, stereography using the two imagers was employed. The RBR is projected using the same method as the cloudmap to progressively higher levels, and at each level the matching error between the two instruments is computed. The cloud height is selected as the height which gives the smallest error. Fig. 3 shows that cloud height computed at times when cloud fraction exceeds 20% compares reasonably with the nearest METAR station located 23km away over a small mountain range in Henderson, NV. The performance of this technique is currently being evaluated.
The motion of the clouds is determined from a cross correlation process between two consecutive images (9) which yields a motion vector field at a single instant in time. In (9) the long term trend in the velocity field was shown to be stable, but there was considerable inter-image fluctuation. To reduce this inter-image fluctuation, a low pass filter is applied

\[ y_n = \sum_j^n \alpha_j x_j + \sum_i^{n-1} \beta_i y_i, \]

\[ \sum_i^{n-1} (\alpha_i + \beta_i) + \alpha_n = 1, \]

\[ \sum_i^n \alpha_i = 0.2, \quad \sum_i^n \beta_i = 0.8, \]

where \( y_i \) are the filtered velocity, \( x_j \) are the raw cross correlation output, and \( \alpha_i \) and \( \beta_i \) are the corresponding weights. The weights logarithmically decrease to zero at ten minutes in the past, and are normalized such that the previous filtered measurements are weighted at 80% and the previous unfiltered velocities are weighted at 20%. This filtering is independently applied to the east-west and north-south velocity. Fig. 4 shows that even when cloud fractions are low, filtering maintains a stable velocity profile.

4. FORECAST METHODOLOGY AND VALIDATION

4.1. Forecast Domain

The forecast domain is selected to be an area that is 4 km × 4 km square centered on the power plant, with a horizontal resolution of 2.5 m which gives individual point forecasts of 6.25 m². This grid is hereinafter "groundmap". The plant occupies 1.3 km² of the domain, which is just over 8% of the forecast area. The cloudmap by contrast has a domain size and resolution that varies linearly with cloud height. The cloudmap covers a larger area when the clouds are higher. It is for this reason that potential cloud forecast horizons vary with height, e.g. fog would cause a short cloud forecast horizon.

4.2. Cloud Transmissivity

Direct solar beam obscuration of each point in the groundmap is determined using solar geometry and a digital elevation model in conjunction with the cloudmap (9), and results in an estimate of ground shadows, hereinafter shadowmap. The effective transmissivity of the clouds obscuring each ground point cannot be determined using the sky imager alone, so recent ground measurements are used to provide an estimate of transmissivity. The cloudmap is binary, so the surface projected shadowmap of the clouds is also binary. Two values of transmissivity, which is also known as clear sky (csk) index \( kt \)

Fig. 2 Illustration of cloudmap projection over the University of California, San Diego campus. Image generated in Google Earth.

Fig. 3 Cloud height profile for November, 12 2011 computed from two sky imagers is compared with the nearest METAR station’s cloud height report.

Fig. 4 Cloud velocity as determined from the filtered maximum cross correlation method on November 12, 2011.
are selected that are characteristic of the observed attenuation of irradiance. The characteristic values are determined from a probability density function generated from the last 10 minutes of data. The distribution of $kt$ is bimodal as indicated in Fig. 5, where the peak near $kt = 1.05$ corresponds to clear sky and the peak near $kt = 0.45$ is the modal cloud transmissivity. The bimodal shape exhibited by $kt$ is not unique to Fig. 5, but occurred on all three days that were tested. It is interesting to note that the small peak near $kt = 1.3$ corresponds to cloud enhancement effects (12).

$$kt = \frac{GHI}{GHI_{esk}},$$

(POA) can be treated as a normalized power output $P_{norm}$:

$$P_{norm} = P / P_{ctr},$$

where $P$ is the power output, and $P_{ctr}$ is an estimated clear sky power output. Assuming standard testing conditions (STC) for rating the panels (13), $P_{ctr}$ can be estimated

$$P_{ctr} = P_{cap} \frac{GI_{esk}}{GI_{stc}},$$

where $P_{cap}$ is the nameplate capacity of the set of panels, $GI_{stc}$ is the STC irradiance taken as 1000 $[W/m^2]$, and $GI_{esk}$ is the clear sky POA irradiance which is computed using the Ineichen clear sky model (14) coupled with the Muneer transposition model as described by Page (15).

Transposition allows the computation of GI from GHI, and requires GHI to be split up into direct and diffuse components. Diffuse fraction was computed from the method of Boland et al. (16). Assuming that actual power conversion efficiencies are similar those in clear sky, the normalized power output is comparable to a POA clear sky index:

$$kt_{poa} = \frac{GI}{GI_{esk}} = P_{norm}.$$  

It was by using equations 3, 4 and 5 that Fig. 5 was constructed.

4.3. Power Output Forecast

For each image that is captured, the cloudmap, and cloud motion is determined. The cloudmap is advected using the cloud velocity at 30 seconds intervals out to a 15 minute forecast horizon. At each of these 31 steps (including the capture time), a shadowmap is constructed and overlayed with the plant footprint. An area weighted POA clear sky index is constructed for the entire plant, and using the $GI_{esk}$ at each forecast interval the power output is determined.

4.4. Validation Metrics

To evaluate the forecast, mean bias error (MBE), mean absolute error (MAE), and root mean square error (RMSE) were computed according to

$$MBE = \frac{1}{(P) N} \sum_{i}^{N} (P_i^f - P_i^a),$$

$$MAE = \frac{1}{(P) N} \sum_{i}^{N} |P_i^f - P_i^a|,$$

Here $P_i^f$ is the forecasted power output and $P_i^a$ is the actual power output.
\[ RMSE = \frac{1}{\langle P \rangle} \left[ \frac{1}{N} \sum_{i}^{N} \left( P_i^f - P_i^p \right)^2 \right]^{1/2}. \]

where the \( P_i^f \) is the \( i^{th} \) forecast power, \( P_i^p \) is the \( i^{th} \) power measurement, and \( \langle P \rangle \) is the average power production over the given day. Normalizing by \( \langle P \rangle \) produces higher relative errors than normalizing by capacity, and in general will give lower errors on days with extended clear periods, and higher errors on mostly cloudy days. The sky imager generates a forecast every 30 seconds so to compare to power, which is collected every second, a 30 second average of power output centered on the image capture time was used. These error metrics are computed for each of the 31 forecast intervals.

5. RESULTS AND CONCLUSIONS

The effect of clouds on the plant is highlighted in Fig. 7. The optical depth of these clouds is high and causes a significant drop in output when they occlude the sun as can be seen in Fig. 7a where the output of the west side of the plant dropped to 10% due to the cloud shown in Fig. 7b.

The forecast performance on the three days tested as a function of forecast horizon is shown in Fig. 8. Due to the way error is computed, the day with the least clouds (Fig. 8a) has the lowest error, and the day with the most clouds (Fig. 8c) has the highest error.

The error is primarily due to shadow positioning offsets in both space and time. The clouds that generate the shadows used for overlaying (as described in section 4.3) are very close to the sun. The shadowband on the TSI masks the most important part of the viewable sky. Better use of stereography can be leveraged to improve cloud field configuration information within the algorithm to generate more accurate shadowmaps. This can help to alleviate some of data lost due to occultation of the sun on the TSI in low cloud conditions. If clouds are higher than about 4,000 m the entire sky area affecting the plant is blocked on both instruments. Furthermore clouds advecting parallel to the shadowband are difficult to predict once they are occluded. To address this, we are currently testing a prototype that has higher resolution and does not have an occultor device.

Fig. 7 A sky image on October 25, 2011 showing clouds with significant optical depth (b) and their impact on power production (a) at the power plant. The power output was multiplied by a random number to protect the confidentiality of the data.

Fig. 8 Forecast error as a function of forecast horizon for (a) October 25, 2011, (b) November 3, 2011 and (c) November 12, 2011. Cloud fraction was lowest in (a), and highest in (c).
blocking the sun. With a smaller obstruction, other errors in the methodology can be further explored and addressed.

The short-term forecasting methodology using ground-based imagery to identify and track clouds, while promising, still requires further work to improve the results in the variety of scenarios required by the solar energy industry.

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7. REFERENCES


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