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CIGRE US National Committee
2022 Grid of the Future Symposium

Estimating the Output of an Inclined Solar Panel Using Irradiance Data Normal to Earth's Surface

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SUMMARY

As more behind the meter solar farms are installed onto the power grid, the actual load on the power grid becomes hidden to the utility because the meters only read the net difference between the native load and the solar generation. This becomes problematic for grid planning since the grid needs to be ready to handle the full native load in the case of a hot and cloudy summer day when load is very high and solar generation is low. This study breaks down solar irradiance into the diffuse components from the ground and sky, and the direct (beam) irradiance. These components are then combined using the Liu-Jordan model to estimate the solar irradiance normal to a tilted surface. This method was then applied to data from a weather station in an area in ComEd's service territory to estimate the solar panel output of a local 2MW metered solar farm. When comparing the predicted generation and measured generation from this solar farm, it was determined that inconsistencies existed within the data set. After reducing the size of the data set to remove bad or incomplete data, this method estimated solar production with an R^2 value of 0.900 with an average absolute value error of 148kW. It can be said from the findings that this methodology has produced efficient results and even has the potential to help determine when a solar farm is not generating as anticipated.

KEYWORDS

Extraterrestrial Solar Radiation, Diffuse Radiation, Direct (beam) Radiation, Liu-Jordan model, Behind-the-Meter-Solar

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1. INTRODUCTION

In recent years, as more people look for clean energy alternatives to fossil fuels and as solar energy becomes an increasingly more economical source of energy, behind the meter solar farms have become considerably more popular. These behind the meter solar panels occur when a meter reads the difference between the native load and the amount of energy generated instead of independently measuring the two. This causes problems for the utility because they do not know the native load on the system for use with grid planning and operation. This potentially can lead to problems on very hot and cloudy summer days when load is very high and solar panels are not generating enough, yet the grid needs serve the load.

Several methods have been proposed to solve this problem. A common technique is to estimate native load by comparing customers to other customers in the area or comparing solar farms to nearby solar farms. One method proposed in [1] estimates native load by comparing customer energy usage to other similar households and comparing solar generation to other similarly oriented systems. A method proposed in [2] uses machine learning to generate a model to estimate behind the meter solar generation based on a select few metered solar sites, weather data, and solar farm location. Another example proposed in [3] divides its customers into ones with and ones without solar behind the meter solar generation in combination with solar irradiance data to disaggregate the solar generation from the native load. A method using measured solar farm output data by proximity to unmetered solar farms to estimate generation was proposed in [4].

A second technique, which is more like the technique described in this paper, uses solar irradiance data to estimate the output of the solar panels. Numerous empirical methods for estimating solar energy radiation on inclined surfaces were evaluated in [5], and it was determined that the Badescu approach tended to underestimate solar irradiance while the Liu-Jordan model performed best during inclement weather. Another study was performed in [6] which considers solar output as a ratio of the measured and nominal irradiance on the solar panel. One study used a Bayesian Structural Time Series model [7] which disaggregates the solar generation and native load at the feeder level of the system with local irradiance measurements.

The technique described in this paper was derived based on the Liu-Jordan model using irradiance data perpendicular to the earth's surface from a weather station to estimate solar generation of inclined solar panels. While similar approaches have been performed in the past and are available commercially as described in [8], our method is easily implemented in code and is only based on irradiance data and solar farm properties without the need to compare customers or solar farms to one another. This method was validated using irradiance data from a weather station in Mendota IL to predict and compare the output to the measured solar generation of a nearby 2MW, metered solar farm.

2. PV OUTPUT ESTIMATION METHODOLOGY

Figure 1 illustrates the process flow of the proposed method for calculating solar farm output based on irradiance data and solar farm properties. Since solar panel output is based on the radiation that strikes normal to the solar panel, this method uses the Liu-Jordan model to calculate solar radiation normal to a tilted surface of inclination (β). The Liu-Jordan model breaks solar radiation into its diffuse and direct (beam) components and sums them together to get the total irradiance normal to a tilted surface (E_t) as defined by:

$$E_t = E_b \cos\theta + E_{d,s}\left(\frac{1+\cos\beta}{2}\right) + E_{d,g}\left(\frac{1-\cos\beta}{2}\right). \quad (1)$$

Diffuse radiation is the radiation that bounces around particles in the earth's atmosphere ($E_{d,s}$) or the ground ($E_{d,g}$) and eventually makes it way to the solar panel while direct radiation (E_b) is the radiation that travels straight from the sun to the solar panel at an angle of incidence (θ). A diagram highlighting these differences is shown in Figure 2.

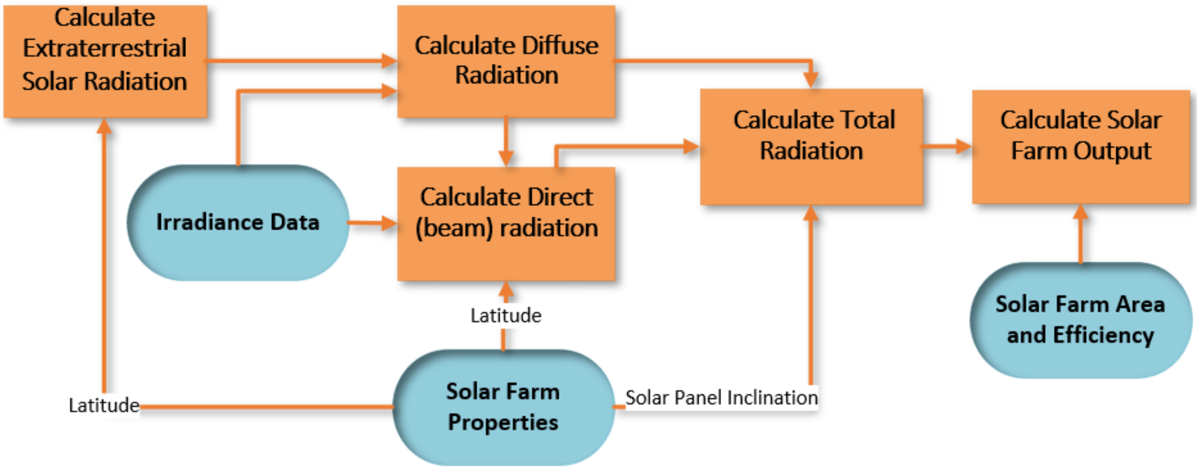

Figure 1: Overview of the proposed methodology using the Liu-Jordan model

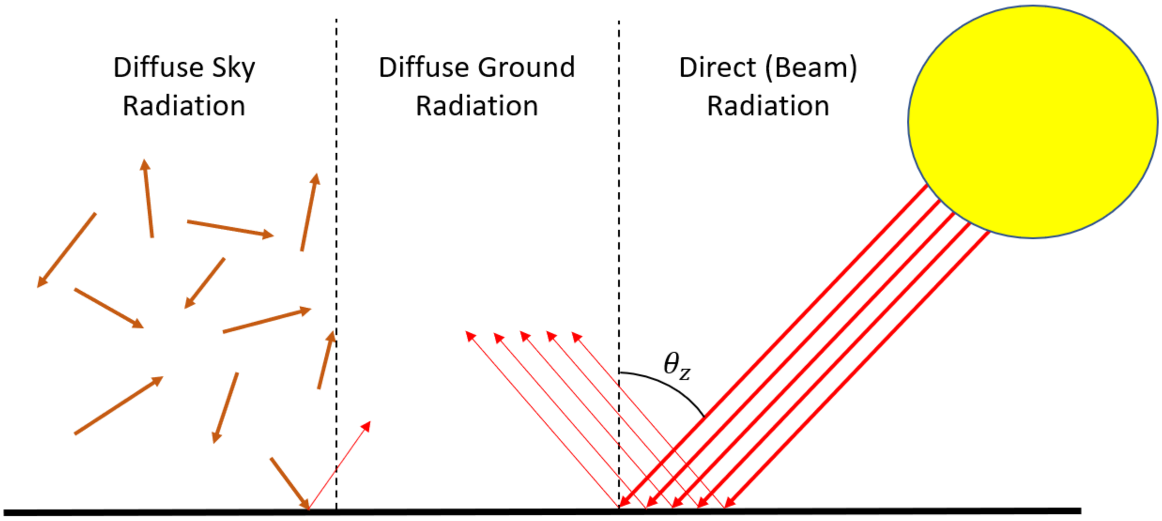

Figure 2: Diagram detailing the difference between diffuse sky radiation, diffuse ground radiation, and direct (beam) radiation with the zenith angle labeled.

2.1. Extraterrestrial Solar Radiation

Extraterrestrial radiation (E_t) is defined as the radiation that striked normal to the earth's atmosphere or would strike normal to the earth's surface assuming the earth did not have an atmosphere. E_t is based on the locations latitude, the time of day, and the time of year.

a) Latitude: In general, as distance from the equator increases, E_t decreases.
b) Time of day: At solar noon, in the middle of the day, E_t is at its maximum. As you get farther from solar noon, E_t decreases all the way to 0 in the nighttime hours.
c) Time of year: Time of year has two effects on E_t. The primary effect is the tilt of the earth towards or away from the sun that causes the seasons. When the sun is tilted toward the sun in the summer, E_t increases, and when the earth is tilted away from the sun in the winter, E_t decreases. Additionally, the earth's distance from the sun changes with time of year having a slight effect on E_t. In the winter, earth is closer to the sun, while in the summer, earth is farther from the sun. The effect varies the solar irradiance striking the earth by ±3.3% [9, 10].

2.2. Diffuse Radiation

The Liu-Jordan model further breaks diffuse radiation into the component from the sky, which is assumed to be uniformly distributed, and the diffuse radiation from the ground. The magnitude of the two components in the Liu-Jordan model are then multiplied by the view factor of the sky/ground onto the inclined solar panel.

a) Diffuse sky radiation: The sky component of diffuse radiation is calculated based on the diffuse fraction. The diffuse fraction is calculated using the Erbs model [10, 11] based on the clearness index. The clearness index is the ratio of measured solar irradiance normal to the earth's surface to the extraterrestrial radiation calculated above. As the solar panel inclination increases, less diffuse sky radiation will strike the solar panel.
b) Diffuse ground radiation: The ground component of diffuse radiation is the product of the measured irradiance and the ground albedo. Ground albedo is the ratio of radiation that gets reflected off the ground. As the inclination of the solar panel increases, a greater portion of the radiation reflected off the ground will strike the solar panel.

2.3. Direct (beam) radiation

The magnitude of the direct radiation normal to the earth's surface is the difference between total radiation and diffuse radiation. To identify the portion that strikes normal to the solar panel, the direct radiation normal to the ground needs to be divided by the cosine of the zenith angle, yielding E_b from equation (1). Then, E_b must be multiplied by the cosine of the angle of incidence. The angle of incidence is a function of:

a) Latitude
b) Time of day
c) Day of year
d) Azimuth angle
e) Inclination angle

Solar farm output is the product of the normal radiation, the solar farm area, and the solar farm efficiency. The predicted output is capped at the inverter's power rating.

3. SIMULATION AND RESULTS

To determine how effectively this method predicts solar output, irradiance data (down-sampled to 8760 – 1 data point/hour) from the Mendota weather station from 11/20/21 to 3/22/22 was used to predict the solar output of a nearby 2MW solar farm. The predicted solar panel output was compared to measured generation data (down-sampled 8760) at the point of interconnection onto the grid after the solar energy goes through an inverter. In this study, solar farm efficiency was assumed to be constant and independent of temperature and solar radiation.

The R^2 value comparing the predicted and measured data is 0.717 with an average absolute value error of 220kW. R^2 is a statistical relationship defining how much of the variation of one parameter can be predicted based on the variations in another parameter where an R^2 of 1 indicates a perfect correlation and an R^2 of 0 indicates no correlation between the two data sets [12]. R^2 is calculated using:

$$R^2 = 1 - SS_{res}/SS_{tot}, \tag{2}$$

where SS_{res} is the sum of squares of the residual errors and SS_{tot} is the total sum of errors [13]. While the R^2 value comparing the predicted solar output to the measured solar output is rather low and the error is high, the data has numerous days in which the solar farm feeder outputs very low power output despite there being high irradiance. An example of a long and continuous region of time with this discrepancy is shown in Figure 3 where the measured irradiance, and therefore the predicted power, are relatively high while the measured power is very low. While this discrepancy has many possible sources, like snow cover on the solar panels or system maintenance, it is unclear what caused these data discrepancies.

To evaluate the method without the poor data, the method was applied once again to data up through 1/22/22, one day before the extended region of poor results started. With this reduced data set, the R^2 value is 0.900, and the average absolute value error is 148kW, which is a significant improvement. A parity plot comparing the measured and predicted values for the reduced data set is shown in Figure 4 which shows that while our method effectively estimates solar output, it tends to overestimate.

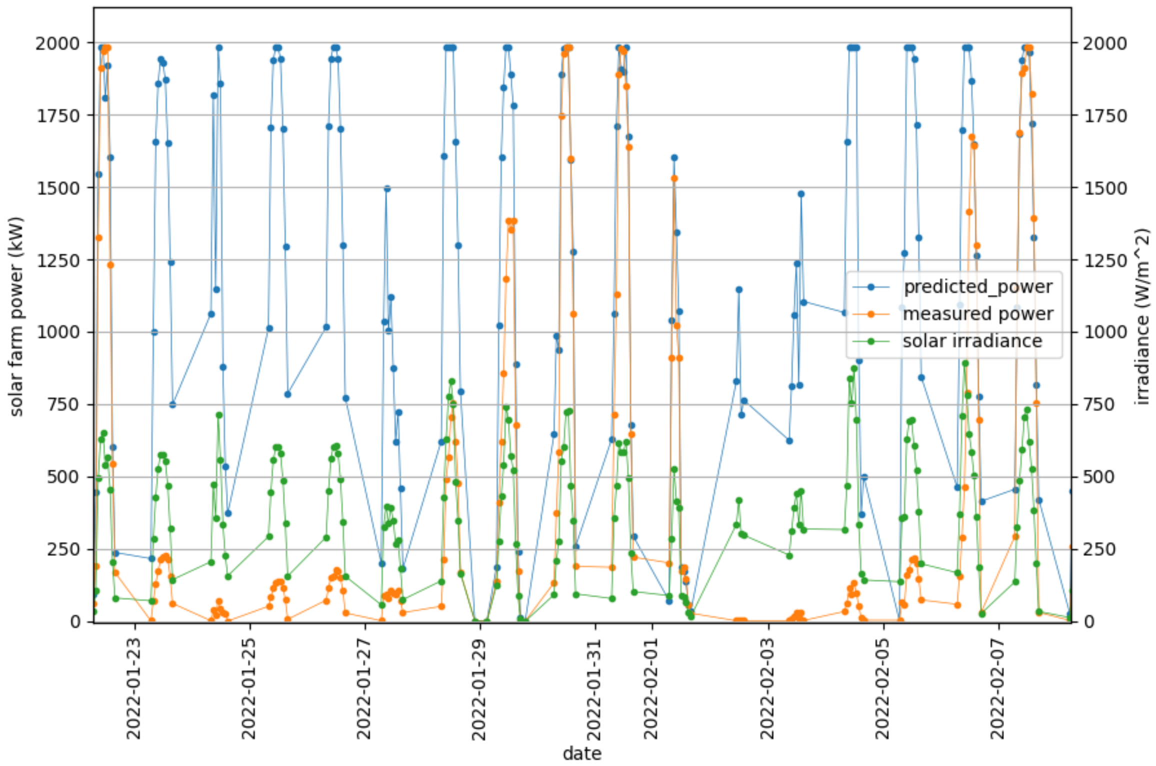

Figure 3: A section of data with a large mismatch between measured and predicted solar power output

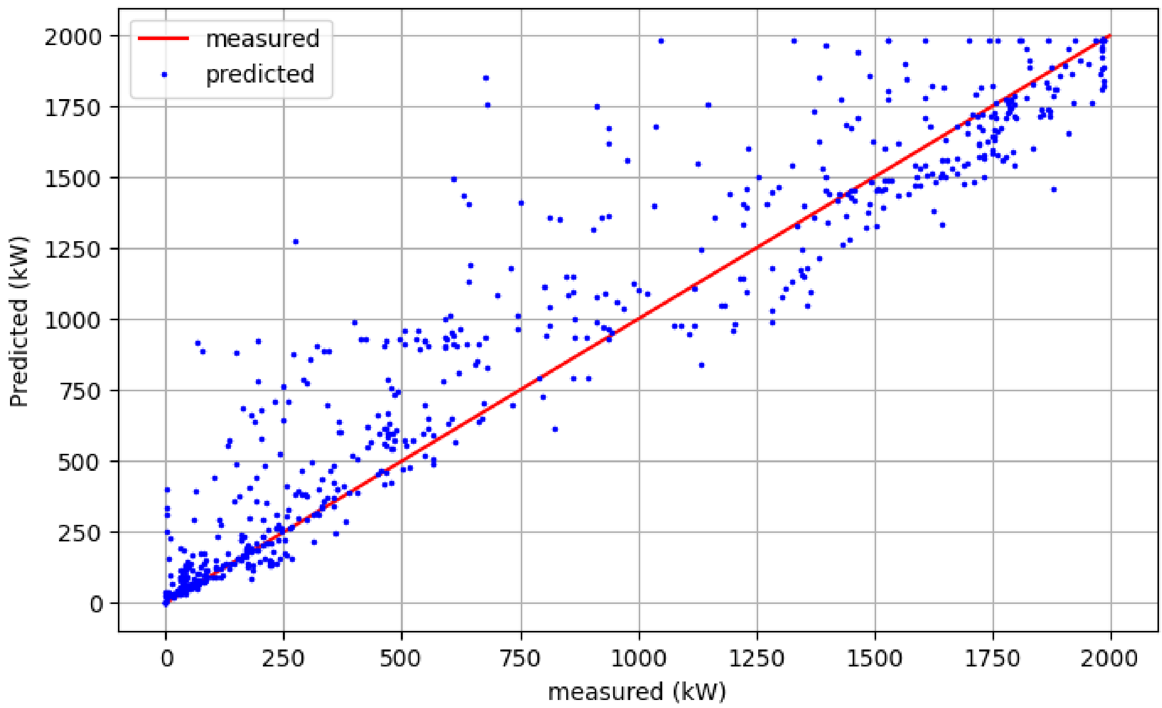

Figure 4: Parity plot comparing measured data and predicted data for the reduced data set

To evaluate this method on a more continuous time basis, the data was then sampled at higher sampling rates. These results are summarized in Table 1: Summary of R^2 and average errors. As the sampling rate was increased, it was found that the relationship between the predicted and measured power became slightly worse when compared to the data sampled less frequently as evident by the R^2 and average arror values. Our method also tends to overestimate the measured power significantly more often than it underestimates as evident by the average error and the parity plot in Figure 4.

Table 1: Summary of R^2 and average errors

Data set	Data points/ hour	R^2	Average abs(error)	Average error
Complete	1	0.717	220	167
	3	0.700	225	184
	5	0.692	225	182
Reduced	1	0.900	148	85
	3	0.882	157	98
	5	0.865	160	99

4. CONCLUSION

The work proposed utilizes the Liu-Jordan model to estimate the output from an inclined solar farm by breaking up the solar irradiance into its diffused and direct components. The advantages of this method are its ability to be easily implemented in code and its ability to estimate solar output based solely on measured irradiance and solar farm properties without the need to compare power data between nearby customers or solar farms.

To demonstrate the effectiveness of this method, the output of a 2MW solar farm was estimated with an R^2 value of 0.900 and an average absolute value error of 148kW. This method has also shown potential in being able to identify when a solar farm is not producing as expected. Despite these effective results, this study is limited by the availability of good data. With a three and a half month long dataset, and with nearly half of it having to be discarded due to large discrepancies between the high irradiance readings and low solar farm output, only two months of data were used in evaluating the validity of this method.

To further validate this technique, another data set encompassing a much larger portion of the year needs to be analyzed. Since peak load occurs during the hottest days of the summer, the accuracy of this technique in the summer is critical, yet the dataset analyzed in this study exclusively comes from the winter. After a larger dataset is analyzed, the results need to be evaluated to determine if this method is sufficiently accurate for predicting native load or if some of the assumptions made need to be re-evaluated to further improve the accuracy of this method.

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