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Solar Resource Assessment Using Micro-Inverter Data

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Abstract

The AC production data from Enphase Energy Inc. micro-inverters for 100 locations in five metropolitan areas were used to derive the location's direct normal irradiance and diffuse horizontal irradiance resource. These data were then used to model the energy production of nearby photovoltaic (PV) systems. Results had small bias errors, and for most locations the results were significantly better than when using satellite-based National Solar Radiation Data Base irradiance data to model PV system energy production.

Using performance data from some of the millions of installed PV modules with micro-inverters offers the opportunity to provide ground-based solar resource data critical for developing PV projects and for the site adjustments of satellite-based irradiance data.

Keywords: *direct and diffuse irradiance, performance, model, micro-inverter.*

1. Introduction

Enphase Energy Inc. micro-inverters have been deployed with millions of photovoltaic (PV) modules and have been providing reliable data with a 5-minute temporal resolution since 2011 (and for some early systems, since 2007). To provide low- or no-cost solar resource data traceable to a ground-based physical measurement at a nearby location, we have developed a method to derive solar resource data from the Enphase Energy Inc. AC power (P_{ac}) data.

First, the global tilted irradiance (GTI), otherwise known as the plane-of-array (POA) irradiance, is determined from the P_{ac} by using inverted PV performance models and solving a quadratic equation for the GTI from the input variables P_{ac}, wind speed (WS), dry-bulb temperature (T_a), and the PV module temperature coefficients (Marion and Smith, 2017a). For values of T_a and WS, we use nearby Automated Surface Observation Station (ASOS) data. Nameplate information is used for the PV module characteristics and temperature coefficients.

Next, the direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) are derived from the GTI using the GTI-DIRINT model (Marion, 2015). This model is a National Renewable Energy Laboratory (NREL) modification of the DIRINT model by Perez et al. (1992), which separates input values of GHI into their DNI and DHI components. The NREL modification substitutes GTI for GHI, and adds an iterative procedure to adjust the global clearness index to improve the derived values of DNI and DHI. Because the GTIs represent a PV measurement, a step is added to the GTI-DIRINT model to correct for the presence of angle-of-incidence (AOI) effects due to increased reflection losses from the PV module front cover when the AOI increases.

Finally, the derived DNI and DHI values (or their global horizontal irradiance (GHI) equivalent) may be used with conventional modeling software—such as PVsyst, Helioscope, and NREL's System Advisor Model (SAM)—to estimate the performance of PV systems of any size, or PV array tilt and azimuth orientation, including tracking.

Previously, we reported validation results of the method for PV modules equipped with micro-inverters and located at NREL (Marion and Smith, 2017b). This work provides an expanded validation of the method using Enphase Energy Inc. micro-inverter data for 100 PV systems located in five climatically diverse metropolitan areas: Phoenix, AZ; Denver, CO; New Orleans, LA; Minneapolis, MN; and Seattle, WA. The use of the method's derived DNI and DHI values to model the energy production of nearby PV systems is compared with the modeled energy production using the SAM and satellite-based irradiance data from the National Solar Radiation Data Base (NSRDB).

2. Data

2.1 Enphase Energy Inc. and Equipment Data

Located between the micro-inverters and Enphase's Enlighten web-based monitoring and analysis software, hardware named Envoy is used for monitoring the performance of the micro-inverters and submitting the data to Enlighten via the internet. At nominal 5-minute intervals, Envoy sequentially polls each micro-inverter in the PV system to obtain the energy produced since last polled.

Enphase Energy Inc. provided the 5-minute energy values to NREL where they were converted to 5-minute averages of P_{ac}. Also provided were the micro-inverter models and the PV module models and manufacturers. This information was used to assign characteristic and nameplate rating data. Micro-inverter models were either the M215 or M250. The PV systems included 46 different PV module models/manufacturers.

2.2 PV Module Azimuths and Tilts

Limited data were available from Enphase Energy Inc. for the PV module tilt and azimuth orientations. Instead, these data were determined using Google Earth views of the PV installations, which were primarily residential. The "ruler" feature was used to estimate the PV module azimuth and the "street view" feature was used to view the roof in profile and to estimate the PV module tilt after considering the street view perspective and adjusting to a standard roof slope (e.g., 4/12, 5/12). If street views were not available or useful, the PV installation was removed from consideration. Uncertainty of the estimated PV azimuths and tilts is ±3°.

2.3 Site Selection

Candidate sites were screened with the use of Google Earth and its street views to find sites where at least one PV module (such as near the roofline) was not shaded by trees or roof structure, other than for times within one hour of sunrise or sunset. More sites were eliminated due to shading for cities with older homes with large trees (Minneapolis and Seattle) and fewer sites were eliminated for cities with PV systems on new construction (Denver and New Orleans) or for cities with fewer and slower growing trees (Phoenix). Twenty sites were selected for both Denver and Phoenix, 46 for New Orleans, but only two for Minneapolis and seven for Seattle. Minneapolis and Seattle also had fewer candidate sites because of fewer PV installations in those areas.

2.4 Micro-Inverter / PV Module Data Selection

For each micro-inverter / PV module of an installation, the average measured P_{ac} was determined by solar azimuth bin. For PV systems with PV modules installed on roofs with multiple azimuth heading (as many as four for some installations), this permitted identifying which micro-inverter / PV modules were installed on which roof orientation. It also permitted identifying and eliminating from selection micro-inverter / PV modules with reduced output due to shading from obstacles or trees. One micro-inverter / PV module was selected for each orientation (if more than one) for each PV system location. Data for PV module azimuth orientations within 45° of south were used with the method to derive the DNI and DHI values. Data for the other orientations were used to validate the ability of the method to estimate the performance of PV systems with different orientations.

2.5 Data Quality Assessment

Invalid data were identified with an error flag to preclude its use in deriving DNI and DHI and when determining the error statistics of the method. Invalid data included P_{ac} values of zero during the day, indicating that the micro-inverter / PV module was not operating. An unreliable internet connection may also influence the P_{ac} values reported by Enphase Energy Inc. because the integrated energy since the last successful call is reported for each successful call. If calls are missed, the P_{ac} values are backfilled using an average P_{ac} value that satisfies the integrated energy. In some cases, nighttime P_{ac} values are greater than zero because of backfilling. These nighttime values were identified with an error flag, as were daytime backfilled P_{ac} values if more than three P_{ac} values were backfilled in an hour.

2.6 Dry-Bulb Temperature and Wind Speed Data

ASOS T_a and WS data from the website at Iowa State University were added to the Enphase Energy Inc. data files (https://mesonet.agron.iastate.edu/request/download.phtml). T_a and WS data permit accounting for the effects of the PV module temperature when using the P_{ac} value to determine the GTI. Typically, a city has multiple ASOS stations. The ASOS station closest to the PV system location was used to provide the T_a and WS data. Because ASOS data are typically hourly samples, T_a and WS were interpolated to the midpoint of the 5-minute intervals.

3. Results

The method was evaluated for the year 2015, which was common for the PV systems considered and available from the NSRDB, which was used with the SAM model to model PV system performance for comparative purposes.

Our previous results showed that southerly orientations provided the best results. Consequently, GTI-DIRINT-derived values of DNI and DHI were only determined for the most southerly oriented PV module of each PV system location. Predominantly, the azimuths of the selected PV modules were within a couple degrees of south, with a couple of exceptions where the azimuth was as much as 45 degrees from south. Additionally, the DNI/DHI datasets for a city are restricted to the top 50% that have the lowest root-mean-square deviation (RMSD) when modeling the monthly AC energy of each PV system in the city that is within 20 km. This step was implemented because the PV module information is from nameplate information or provided by the installer/owner and may not be 100% accurate, as indicated by some micro-inverter / PV modules being much better than others in predicting the performance of their neighbors.

Each set of the derived DNI and DHI values were then used to model the performance (P_{ac}) of each of the other PV systems in the city. For comparison with a conventional PV system model, the AC energy of each of the PV systems was modeled using NREL's SAM and satellite-derived NSRDB irradiance data for 2015. The NSRDB data were downloaded using the NSRDB viewer (https://nsrdb.nrel.gov/nsrdb-viewer) and the appropriate 4×4-km spatial-resolution dataset was selected to match each PV system's location.

Tables 1 through 4 provide mean bias deviation (MBD) and RMSD values for the monthly and annual modeled P_{ac} for the two methods. The results are expressed as a percentage of the average of the measured data (using Enphase P_{ac} data). The # months and # years values in the tables represent the number of modeled months or years that were used to determine the statistics. When using the SAM and NSRDB (Tab. 2 and Tab. 4), the values correspond to the PV system being modeled just once using the closest NSRDB. When using the PV-derived irradiance data, the values are generally much greater because each PV derived irradiance data set for a city was used to model the performance of other PV systems in the same city (Tab. 1 and Tab. 3).

By considering the error for a 95% confidence interval to be twice the RMSDs from Tables 1 and 2 for all 104 systems, the error for providing monthly estimates of the AC energy is ±11.2% for the PV-derived data method and ±19.0% for the method using SAM and the NSRDB, a difference of 7.8% absolute.

Similarly, from the RMSDs from Tables 3 and 4, the error for providing annual estimates of the AC energy is ±8.6% for the PV-derived data method and ±17.2% for the method using SAM and NSRDB, a difference of 8.6% absolute.

Tab. 1: Mean Bias Deviation (MBD) and Root-Mean-Square Deviation (RMSD) for Modeled Monthly AC Energy Production using PV-Derived Irradiance Data.

Statistic	PV-Derived Method					
	Denver	Minneapolis	New Orleans	Phoenix	Seattle	ALL
# systems	26	2	50	19	7	104
# months	2256	24	10767	1421	216	14684
Mean (kWh/kW)	117.1	104.9	113.2	135.6	97.7	115.8
MBD (%)	-0.2	-1.2	-0.2	-1.1	-1.2	-0.3
RMSD (%)	6.9	4.4	5.5	3.8	5.0	5.6

Tab. 2: Mean Bias Deviation (MBD) and Root-Mean-Square Deviation (RMSD) for Modeled Monthly AC Energy Production using NSRDB Satellite-Derived Irradiance Data.

Statistic	SAM and NSRDB					
	Denver	Minneapolis	New Orleans	Phoenix	Seattle	ALL
# systems	26	2	50	19	7	104
# months	280	24	591	264	84	1243
Mean (kWh/kW)	117.9	106.5	115.9	140.2	99.9	120.3
MBD (%)	11.1	13.6	7.7	0.2	8.8	6.7
RMSD (%)	13.2	15.9	9.3	4.1	10.1	9.5

Tab. 3: Mean Bias Deviation (MBD) and Root-Mean-Square Deviation (RMSD) for Modeled Annual AC Energy Production using PV-Derived Irradiance Data.

Statistic	PV Derived Method					
	Denver	Minneapolis	New Orleans	Phoenix	Seattle	ALL
# systems	26	2	50	19	7	104
# years	230	2	921	127	18	1298
Mean (kWh/kW)	1,262.3	1,259.2	1,340.4	1,478	1,172.1	1,337.6
MBD (%)	-0.2	-1.2	-0.2	-1.2	-1.2	-0.3
RMSD (%)	3.6	1.5	4.5	3.2	3.7	4.3

Tab. 4: Mean Bias Deviation (MBD) and Root-Mean-Square Deviation (RMSD) for Modeled Annual AC Energy Production using NSRDB Satellite-Derived Irradiance Data.

Statistic	SAM and NSRDB					
	Denver	Minneapolis	New Orleans	Phoenix	Seattle	ALL
# systems	26	2	50	19	7	104
# years	26	2	50	19	7	104
Mean (kWh/kW)	1,323.7	1,277.9	1,379.6	1,630.5	1,198.3	1,397.3
MBD (%)	11.1	13.6	7.7	-0.9	8.8	6.8
RMSD (%)	11.7	14.3	8.6	2.2	9.5	8.6

The MBDs were small values for all cities when using the PV-derived irradiance data and not seasonally dependent, whereas when using the NSRDB, this was only true for the sunniest city, Phoenix. For the other cloudier cities, the MBDs were larger positive values and exhibited seasonal biases.

Figure 1 shows the seasonal dependence of the MBDs when using the NSRDB to model the performance of the PV systems located in Seattle. The MBDs are shown greatest in the winter months. For comparison, Figure 2 shows little or no seasonal dependence of the MBDs when using the PV-derived irradiance data to model the performance of other PV systems located in Seattle. Figure 3 shows the seasonal dependence of the MBDs when using the NSRDB to model the performance of the PV systems located in New Orleans. The MBDs are shown to oscillate over the year, with largest MBDs in May and December.

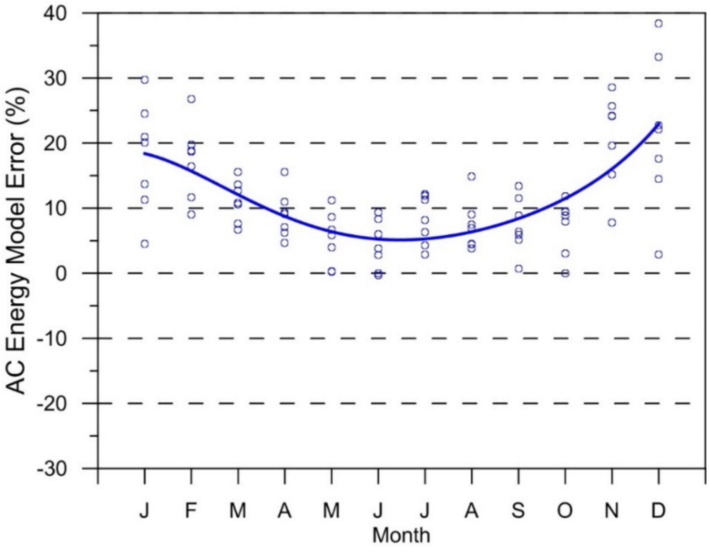

Fig. 1: MBDs for monthly AC energy production modeled using SAM and the NSRDB for PV systems in Seattle.

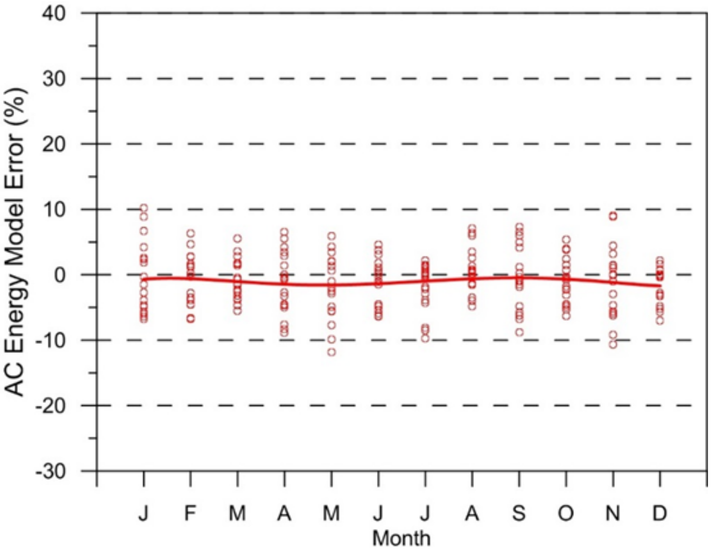

Fig. 2: MBDs for monthly AC energy production modeled using PV-derived irradiance data for PV systems in Seattle.

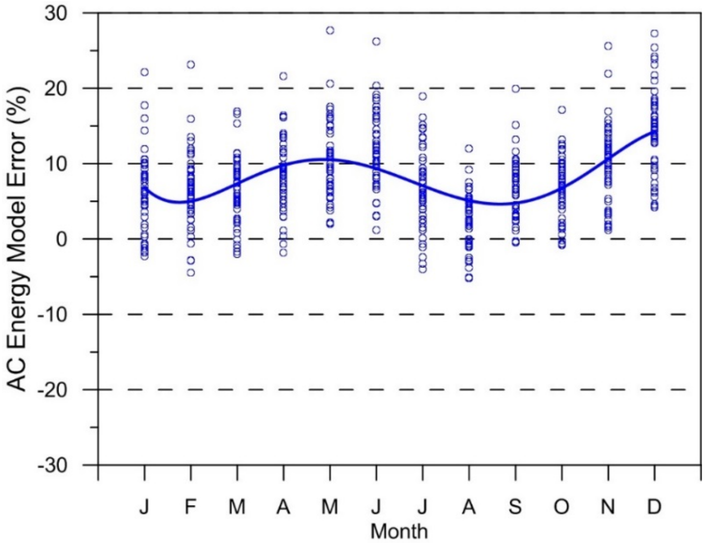

Fig. 3: MBDs for monthly AC energy production modeled using SAM and the NSRDB for PV systems in New Orleans.

4. Summary

Using PV performance data from PV modules with micro-inverters affords the opportunity to provide ground-based solar resource values of DNI and DHI critical for developing PV projects and for validating and adjusting (rebalancing) satellite-derived irradiance data.

Compared to using the SAM and the NSRDB for modeling the annual performance of the PV systems, the use of the PV-derived irradiance data reduced the relative modeling error by about 50% for 104 PV systems located in five metropolitan areas.

The method used data available as-is from Enphase Energy Inc. Further error reduction is possible by reducing errors associated with inputs to the method, by:

- Measuring the PV module's actual performance at Standard Test Conditions instead of using a nameplate rating. (Perhaps post-deployment if a deployed PV system of interest is identified).
- Visiting sites to verify PV module tilt and azimuth angles and the absence of shading.
- Measuring the AC energy production with a revenue-grade smart meter (±0.2% uncertainty vs ±2.5% uncertainty as available from Enphase Energy Inc.).

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