Realtime Decomposition of Site-Measured Solar Irradiance Using Machine Learning for Bifacial System Performance Characterization

Aron P. Dobos*, John M. Obrecht* and Zoe C. DeFreitas*
*Envision Digital Corporation, Redwood City, CA, 94065

***Abstract*—This work presents a method for decomposing realtime on-site measured plane of array (POA) and global horizontal (GHI) irradiance from pyranometers into beam and diffuse components. A machine learning method is applied in conjunction with typical metereological year (TMY) irradiance data to facilitate reliable irradiance decomposition of five minute measured data, a regime in which conventional decomposition methods like GTI-DIRINT sometimes struggle. The approach is combined with view factor models of rear side irradiance for bifacial systems to reliably calculate performance ratio and other metrics. Validation of the method on bifacial utility-scale solar power plant data shows credible results.**

***Index Terms*—solar irradiance, plane of array, decomposition, photovoltaic performance analysis, bifacial PV**

I. Introduction

In the context of long term photovoltaic system performance monitoring and analytics, it is essential to reliably calculate key performance indicators (KPIs) and metrics of solar plant operation such as weather corrected performance ratio (PR), among others. Bifacial systems present unique challenges for performance monitoring and analytics, due to the well documented complexities of evaluating the rear side contribution to overall system perfomance under continuously varying operating conditions.

While we suspect that nearly all future utility scale bifacial systems will have at least some form of direct measurement of rear-side irradiance, it is not clear at this time whether the data from backside pyranometers are sufficiently representative of average conditions across large arrays to from the basis of site-level performance predictions. Anecdotally, solar instrumentation vendors have suggested sensor placement at various places along tracker rows, such as the "1/3" rule [1], since the specific location select may affect measured values significantly. Therefore, in our work, we have taken a model-based approach to rear side irradiance characterization that is less sensitive to system-specific design particulars and is intended to yield a more "representative" value for rear-side irradiance on large systems with many fixed or tracking rows. Common two dimensional view factor models of rear irradiance, such as NREL's *bifacialvf* [3] and *pvfactors* [4], both require irradiance components of beam and diffuse to drive the calculations. Since beam and diffuse irradiance are almost never available from on-site measurements, additional modeling is needed to decompose them from site-measured plane-of-array and global horizontal pyranometer data.

GTI-DIRINT [5], a popular irradiance decomposition model developed by NREL and integrated in the System Advisor Model [2] photovoltaic modeling software, has been shown to yield reliable results over monthly and annual time scales for energy modeling purposes. However, it has not been generally applied to high temporal resolution power modeling situations, such as near real-time operations performance monitoring with one or five minute data. Our investigation suggests that there are internal discontinuities in the GTI-DIRINT model that may compromise decomposition results at these time scales.

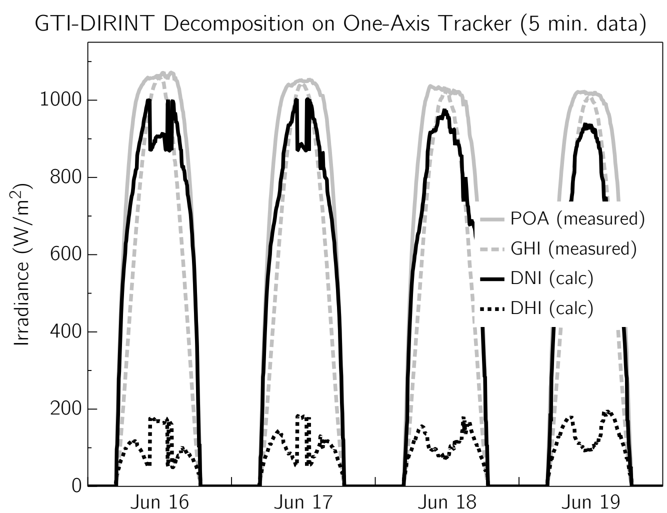

Fig. 1. Representative GTI-DIRINT decomposition for a one-axis tracker system in California with clear shortcomings in 5 minute data estimations.

Representative GTI-DIRINT results for a one-axis tracking system for a few days in June are shown in Fig. 1, and a number of concerns may be observed. There are some clear discontinuities in both beam and diffuse around solar noon, particularly on many clear sky days. The diffuse horizontal (DHI) irradiance also presents with a "double-hump" profile, which is known to be non-physical. Consequently, we have developed a new approach to decomposition using machine learning and typical meterological year data to allow for more reliable realtime rear side irradiance estimation on bifacial systems, described subsequently.

II. Approach

For developing our real time decomposition model, the catalogue of available input data includes:

- Hourly TMY file that includes DNI and DHI for the plant location
- Site-measured GHI and POA, usually at 5 minute interval

- Basic system design specifications, including array type (fixed, tracker), orientation, and GCR

The decomposition approach proposed is as follows:

1) Use standard transposition models to calculate hourly POA and GHI from the hourly TMY beam and diffuse data and system specifications
2) Train a machine learning model on the hourly data to predict DNI from GHI, POA, and day of year
3) Apply the same trained model to the 5 minute site-measured GHI and POA to calculate a 5 minute DNI
4) Use transposition relationships to calculate 5 minute DHI
5) Apply an iterative process to minimize the residual between model-predicted POA and site-measured POA
6) Use the decomposed 5 minute beam and diffuse to drive the view factor models of bifacial rear side irradiance

The central assumption in our approach is that there is enough "information" in the hourly TMY data about the relationships between beam and diffuse for a specific location that extrapolating a model trained on hourly typical year data to be used on 5 minute specific-year on-site data is appropriate. In addition, for tracking systems, we assume that conventional backtracking algorithms may sufficiently model an "average" site plane of array orientation. For tracker systems with independent row architecture deploying advanced row-to-row shade avoidance for uneven terrain and diffuse light optimization algorithms, this assumption may be called into question for any specific row - a further reason why a measurement of rear side irradiance at a single point in the plant may not be appropriate.

For our model development, we take measured data from a utility-scale north-south aligned one-axis tracking site in California with a GCR of 0.46. We select a random forest regression (RFR) model for its general purpose utility, simplicity, robustness, and good performance. As observed in Fig. 2, the R^2 is very high showing that the RFR model can reliably predict the hourly DNI value after training on the hourly TMY file.

Applying the hourly-trained model to five minute data yields promising results in both clear- and dynamic- sky conditions, even prior to iterative residual correction, as indicated in Fig. 3. Fortunately, the large discontinuities and double-hump diffuse observed in the GTI-DIRINT result do not appear. While some minor discontinuous behavor can be seen in the beam irradiance, the effect seems relatively minor and may be improved in further refinement of the machine learning approach.

Next, we apply an iterative correction where the model-predicted DNI is updated to minimize the residual between model-predicted and site-measured POA. We enfore that the corrected DNI is greater than zero, and iterate until there is less than 1 % change between iterations. Fig. 4 shows the expected tightening of the R^2 between calculated and measured 5 minute POA. The DNI correction appears to reduce spikes in DNI,

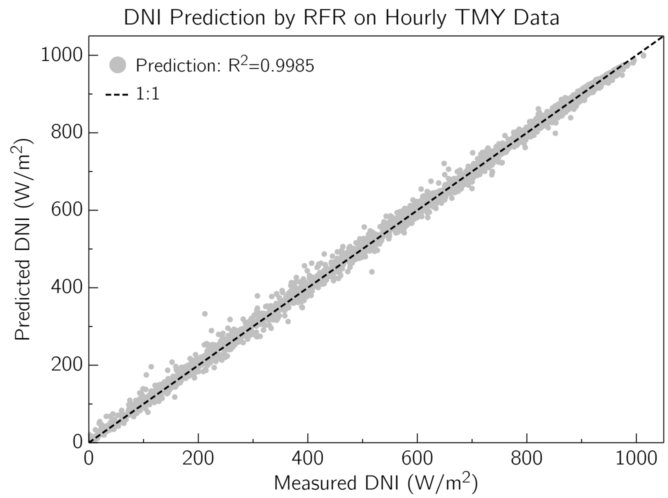

Fig. 2. Confirmation of the RFR model's ability to predict DNI after training on hourly TMY data.

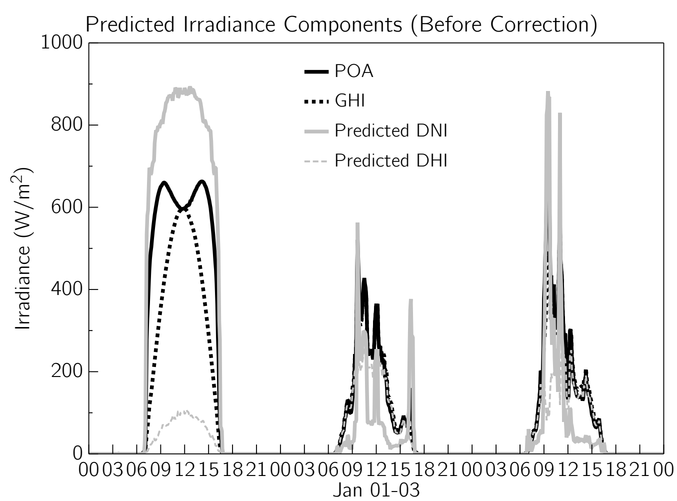

Fig. 3. Predicted 5 minute beam and diffuse irradiance from site-measured GHI and DNI using an RFR model trained on hourly TMY data.

after which the DHI is recalculated to maintain coherence among the three irradiance components.

Finally, we take the corrected 5 minute decomposed beam and diffuse irradiance and apply the NREL *bifacialvf* 2D view factor model to estimate the rear side irradiance on this tracking system.

As observed in Fig. 5, the result appears promising. The profile of the rear side irradiance matches what one would intuitively expect on a tracking system, both in clear sky and diffuse or dynamic conditions. Accumulated on an annual basis, the rear side contributes approximately an additional 7 % irradiance gain, which after a typical bifaciality factor of 0.65, is suggestive of a 4.5 % energy yield gain from the rear side.

In the next section, we explore how the method enables

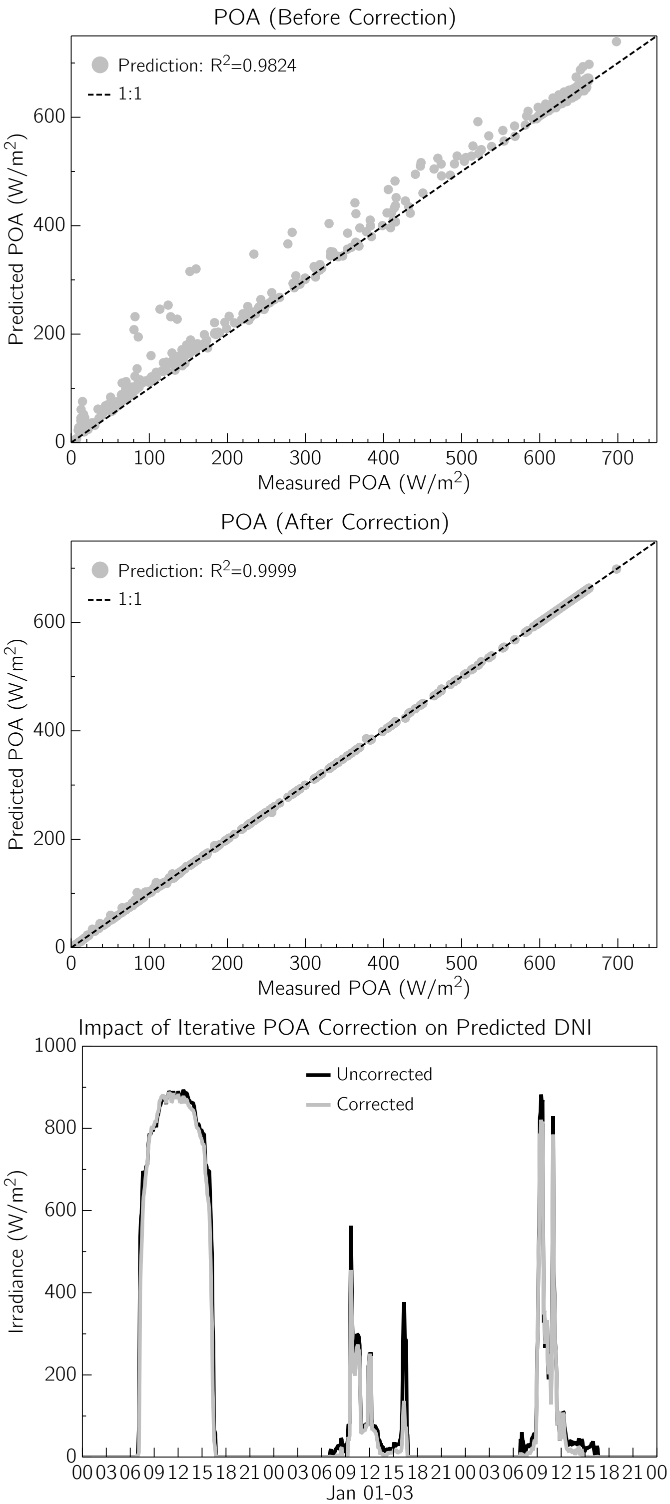

Fig. 4. Before and after iterative correction to the predicted DNI values.

improved calculation of standard solar KPIs.

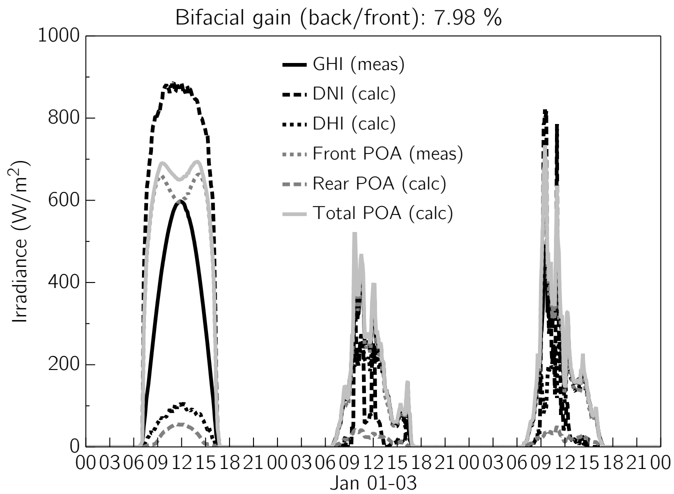

Fig. 5. Rear side plane of array irradiance estimation results.

III. Bifacial Performance Ratio

A key performance metric for solar power plants is the performance ratio (PR), often calculated using the standard weather correction approach described in [6] and indicated in Eqn. 1.

$$PR_{wc} = \frac{\sum_i EN_{AC_i}}{\sum_i \left[P_{dc0} \left(\frac{G_{POA_i}}{1000} \right) \left(1 - \frac{\delta}{100} \left(T_{c,avg} - T_{c_i} \right) \right) \right]} \quad (1)$$

This approach was originally conceived for monofacial systems, under the assumption of readily available plane of array irradiance measured on site, as well as normal flash test module ratings at standard test conditions. Bifacial modules complicate the situation by their nameplate rating still being front side only with an indicated bifaciality factor, and high degrees of nonuniformity in measured rear side irradiance, when a rear irradiance sensor is even available. By leaving the denominator unchanged, the higher bifacial energy yield will frequently lead to performance ratios in excess of 100 %, and make it difficult to compare relative performance in solar fleets including both monofacial and bifacial systems.

Our proposed solution is as follows:

1) Retain the front side DC rating P_{dc0}
2) Replace G_{POA} with the total front+rear POA
3) Use a modeled rear POA using the realtime decomposition approach described in the previous section combined with a view factor model to estimate a representative field-average rear irradiance, rather than relying on a single point source measurement

It is fair to debate the merits of the third point, and further investigation is probably warranted to decide whether the modeled rear irradiance yields the desired and credible outcome, particularly on one axis tracker systems deploying advanced tracking algorithms. Regardless, we can see that when comparing daily PRwc values across a year, as well as the annual averages, the proposed solution yields a much more credible solar performance KPI result for a bifacial site in Minnesota, USA.

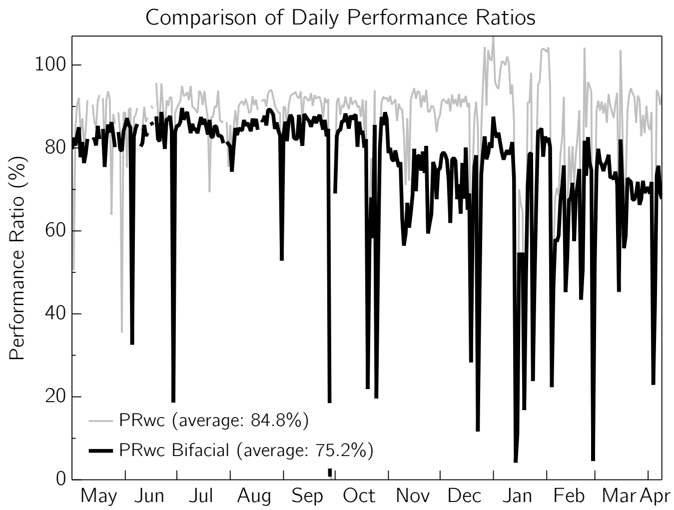

Fig. 6. Comparison of daily PRwc trend.

TABLE I
COMPARISON OF ANNUAL WEATHER-CORRECTED PERFORMANCE RATIO FOR FIVE BIFACIAL SITES IN MINNESOTA, USA.

Site	PRwc (%)	PRwc Bifacial (%)
Bifacial-1	84.8	75.2
Bifacial-2	87.4	72.9
Bifacial-3	87.8	77.3
Bifacial-4	91.1	82.1
Bifacial-5	82.7	76.0
Average	86.7	76.7

Comparing "regular PRwc" and "Bifacial PRwc" results across five bifacial plants shows similar patterns: that standard KPI calculations overpredict plant performance ratios and must be corrected for the inclusion of site representative rear side irradiance contributions.

IV. CONCLUSION

This paper presents a machine learning approach to adapt on-site measurements of plane of array irradiance and global horizontal irradiance to beam and diffuse components to enable estimation of rear-side gains and performance ratios of bifacial systems. Leveraging location specific irradiance component characteristics inherently contained within the data of hourly TMY files for model training, the approach shows good results for high frequency data, and enables credible calculation of standard performance metrics like weather-corrected performance ratio. An evolution of this method is currently applied to bifacial performance analytics algorithms in Envision Digital's Ensight Solar advanced analytics software solution [7].

REFERENCES

[1] Discussions with technical staff at Campbell Scientific, 2019.

[2] System Advisor Model (SAM). National Renewable Energy Laboratory, Version 2020.2.29. [online] http://sam.nrel.gov

[3] Marion, B., MacAlpine, S., Deline, C., Asgharzadeh, A., Toor, F., Riley, D., Hansen, C. (2017). A Practical Irradiance Model for Bifacial PV Modules: Preprint. In 44th IEEE Photovoltaic Specialists Conference. Washington, DC. https://www.nrel.gov/docs/fy17osti/67847.pdf. NREL/CP-5J00-67847

[4] Anoma, M., Jacob, D., Bourne, B.C., Scholl, J.A., Riley, D.M. and Hansen, C.W., 2017. View Factor Model and Validation for Bifacial PV and Diffuse Shade on Single-Axis Trackers. In 44th IEEE Photovoltaic Specialist Conference.

[5] Marion, B.; A model for deriving the direct normal and diffuse horizontal irradiance from the global tilted irradiance. Solar Energy, vol.122, pp.1037-1046, Dec. 2015.

[6] Dierauf, T. D.; Growitz, A.; Kurtz, S.; Cruz, J. L. B.; Riley, E.; Hansen, C.; *Weather-Corrected Performance Ratio*, NREL TP/5200-57991, 2013.

[7] Envision Ensight Solar. Envision Digital Corporation, Version 2.7. [online] https://www.envision-digital.com/enos-advanced-analytics-for-solar/