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APPLICATIONS

Measured and estimated performance of a fleet of shaded photovoltaic systems with string and module-level inverters

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ABSTRACT

Shade obstructions can significantly impact the performance of photovoltaic (PV) systems. Although there are many models for partially shaded PV arrays, there is a lack of information available regarding their accuracy and uncertainty when compared with actual field performance. This work assesses the recorded performance of 46 residential PV systems, equipped with either string-level or module-level inverters, under a variety of shading conditions. We compare their energy production data to annual PV performance predictions, with a focus on the practical models developed here for National Renewable Energy Laboratory’s SYSTEM ADVISOR MODEL software. This includes assessment of shade extent on each PV system by using traditional onsite surveys and newer 3D obstruction modelling. The electrical impact of shade is modelled by either a nonlinear performance model or assumption of linear impact with shade extent, depending on the inverter type. When applied to the fleet of residential PV systems, performance is predicted with median annual bias errors of 2.5% or less, for systems with up to 20% estimated shading loss. The partial shade models are not found to add appreciable uncertainty to annual predictions of energy production for this fleet of systems but do introduce a monthly root-mean-square error of approximately 4%–9% due to seasonal effects. Use of a detailed 3D model results in similar or improved accuracy over site survey methods, indicating that, with proper description of shade obstructions, modelling of partially shaded PV arrays can be done completely remotely, potentially saving time and cost. Published 2017. This article is a U.S. Government work and is in the public domain in the USA.

KEYWORDS

modelling; photovoltaic systems; shading; solar energy

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INTRODUCTION

Solar photovoltaic (PV) distributed generation has certain advantages over large-scale PV systems such as reduced transmission and distribution cost [1,2] and leveraging of existing building stock [3–5]. However, building geometries and landscapes of distributed generation PV systems in urban and suburban environments often create situations in which arrays are partially shaded during a portion of their operating hours. Partial shading, though not ideal, does not necessarily preclude the financial viability of a PV installation; the resulting energy losses may be mitigated by using distributed maximum-power point tracking (DMPPT) electronics [6–9], or the shade loss may be insignificant, depending on the location and extent of shade obstructions relative to the array. To determine the value to the customer, we must accurately predict the impact of partial shading on a proposed PV system’s performance, without adding undue time or complexity to the PV modelling process.

The initial challenge in estimating the performance impact of nearby shade obstructions is to accurately model the position of the obstruction and the reduction in irradiance across the PV system from resulting shadows. Historically, this estimation has been accomplished by using onsite survey imaging tools [10,11]. Other increasingly popular methods include 3D computer-aided design (CAD) modelling [12,13], as well as aerial Light Detection and Ranging analysis [14,15] and geographic information systems analysis [16,17], particularly for large-scale estimation of PV potential. In this work, we use the 3D CAD methodology in National Renewable Energy
Laboratory (NREL)’s SYSTEM ADVISOR MODEL (SAM) [18] to describe obstruction shade conditions and compare this to use of onsite shade surveys taken with a Solmetric SunEye.

A second challenge is to identify the PV performance impact from reduced and nonuniform irradiance across the PV system. Partial shade losses arise from both (i) the reduced irradiance within the shaded area and (ii) current and voltage mismatch between shaded and unshaded sections of the PV system [12,13]. The loss from reduced irradiance cannot be recovered, but mismatch losses may be recovered by the use of DMPPT electronics within the system [6–9], as shown in Figure 1.

Therefore, it is important to understand the system topology before attempting to calculate shade and mismatch performance losses. Systems equipped with central inverters without DMPPT suffer greater-than-linear losses under shaded conditions. These losses can be calculated directly by tabulating the current–voltage ($I$–$V$) curve response at the cell or module level [13,19–22]. This approach provides a full and accurate solution, but computation time is typically too great for integration into annual performance simulation programs such as NREL’s SAM or PVWATTS [23].

Many previous efforts have simplified the question of shade’s impact on performance, either by restricting the shade geometry to that of regular inter-row self-shading [24,25], simplifying the module $I$–$V$ curve description [26,27], or applying an empirical ‘shade factor’ to the area of shade extent [19,28]. Other recent works [29,30] have derived simplified mathematical expressions for calculation of the maximum power points of partially shaded PV systems, with limited validation under a tightly controlled set of test cases.

Here, we build on a previous description of a hybrid solution [31] that precomputes loss factors for a wide variety of shading scenarios, based on a detailed cell-level model [32]. By storing the results of these complicated shade calculations in a lookup table, the time required to access shade-loss values for an annual simulation is reduced from hours to seconds. This method is currently available through NREL’s SAM software, and it is also available as a standalone open-source module online [18]. We provide additional detail on this method, including comparison to other models, and also describe the much simpler scenario of PV system performance where loss is proportional to the extent of shade on the PV system, as would be the case with the use of DMPPT equipment.

To assess the accuracy of partial shade simulation tools and methods, as well as the impact of partial shading on the uncertainty of PV performance prediction, production data were obtained from 46 different residential PV systems—23 that included a single central or string inverter and 23 equipped with microinverters on each PV module. The extent of shade on each system ranges from unshaded (0% expected shade loss) to heavily shaded (20% expected shade loss). This work is the first to compare full, annual simulations of a fleet of partially shaded PV systems’ performance to annual production data, with an emphasis on practical shade modelling methodologies, and to analyse the resulting model uncertainty associated with partial shading. The results indicate that the uncertainty associated
with shade losses can be on the order of other sources of modelling uncertainty, demonstrating that partially shaded PV systems can be modelled and assessed with a similar level of effort and confidence as their unshaded counterparts.

SHAADOW POSITION ESTIMATION

In this work, we determined estimates of shade extent for the aforementioned PV systems by using two different methods: 3D CAD modelling of nearby obstructions and rooftop site survey imaging.

CAD modelling

Three-dimensional CAD modelling of shadows is done in SAM, using the software’s 3D shade calculator tool. During each simulated hour, we consider nominal incident plane-of-array irradiance \( G = G_d + G_r + G_b \), where \( G_d \) is the diffuse, \( G_r \) is the ground-reflected, and \( G_b \) is the beam irradiance component. In typical approaches, including the one used in SAM, \( G \) is calculated by transposing a horizontal resource to the tilted plane [33,34].

Diffuse irradiance \( G_d \) can be reduced by horizon obstructions that limit the field of view of the solar collector to the open sky dome. This loss fraction is independent of solar position and is described in greater detail in Appendix A. While \( G_r \) is also reduced by horizon obstructions, the effect is modest compared with other irradiance terms and is therefore neglected in this approach.

Beam irradiance \( G_b \) is blocked by near-shade and far-shade obstructions; in SAM, the extent to which the array experiences direct-beam shading from nearby structures is determined by the user-input, 3D shade scene, which includes the active array area (divided into subarrays and strings, if applicable) as well as various shading obstacles such as trees, roofs, and other nearby opaque objects. Hourly beam irradiance shading fractions are calculated for each string of the array on a by-area basis by using the shade scene and a standard sun position algorithm [35] to map shadows onto the array. In this method, shading obstructions are assumed to be fully opaque to beam irradiance, which means that, at any given time, the array operates under only two light levels, shaded and unshaded.

CAD modelling sensitivity

To investigate the sensitivity of 3D modelling techniques to errors in obstruction size and placement, SAM simulations are conducted of a south-facing PV system under two hypothetical installation conditions: moderately shaded (one tree) and heavily shaded (three trees), shown in Figure 2. The two scenarios in Figure 2 are considered a ‘base case’, and the trees’ diameters and heights are subsequently increased or decreased by 10% or 25% of their base values, to evaluate their impact on annual cumulative irradiance or insolation. The base cases for the moderate and high shading conditions represent annual insolations of 1961 kWh/m\(^2\) and 1866 kWh/m\(^2\) respectively (Table I). These insolations were found to be quite sensitive to the effect of obstruction placement, changing by as much as ±1.5% for the moderate shading case and as much as ±3% for the high shading case. This indicates that the simulation shading scenes must be developed with as much accuracy as possible because relatively small differences in shade obstacles can lead to significant differences in calculated irradiance.

Aerial imagery shade estimation

Another method for shade estimation uses aerial imagery. Aerial surveys are able to quickly cover large portions of a metropolitan or rural area, and they are often used as part of a geographic information systems program for municipalities. Although a typical aerial overflight produces flat images, 3D data can be obtained from special instrumentation, such as stereo photogrammetry or Light Detection and Ranging [12–15]. Previous comparisons of the solar access values (SAVs) from aerial imagery site survey
techniques versus those generated by the Solmetric SunEye [36,37] have shown that the methods give statistically equivalent results. Specifically, these previous validation efforts have found statistical equivalence between aerial imagery techniques and rooftop site surveys within ±3% on an annual basis and 10% on a monthly basis for a given PV installation.

**Rooftop site surveys**

An alternate method for shade estimation is a rooftop site survey, which requires access to the PV rooftop to determine shading based on local imagery. The use of a stereo-fisheye image to determine a shadow’s extent is fully addressed in Ref. [38]. A general SAV $SA(t)$ is assigned for each timestep $t$, where

$$SA(t) = \frac{(1 - S(t))G_b(t) + G_d(t) + G_f(t)}{G_b(t) + G_d(t) + G_f(t)}$$

(1)

Here, $S(t)$ is the ratio of shaded to total area averaged across the entire array at timestep $t$. For each timestep, effective array irradiance $G_{eff}^t$ is equal to $G_{eff}^t = G(t) \cdot SA(t)$. These values are often summed or averaged across monthly and annual periods to create seasonal and overall solar access and irradiance profiles.

A similar approach is taken with the Solmetric SunEye survey tool [39], except solar access $SA_{suneye}(t)$ does not account for diffuse and reflected irradiance. Instead,

$$SA_{suneye}(t) = \frac{(1 - S(t))G(t)}{G(t)} = 1 - S(t)$$

(2)

Equation (1) can be considered a true accounting of the average irradiance present across the PV system; the presence of far shade only blocks the direct-beam irradiance component within the shadow’s extent, and diffuse irradiance is not affected. Equation (2) is a more conservative estimate of solar access. The shading factor is applied to all components of irradiance, including diffuse and reflected irradiance. This may seem nonphysical, but for some conditions, it more closely matches the electrical behaviour of a PV system under partial shading conditions. In particular, small amounts of shade on a single-string PV system can cause a bypass diode to turn on, which effectively negates all irradiance—beam and diffuse—present on that submodule. Therefore, Eqn (2) combines an irradiance and electrical model for monthly and annual shade impact estimation. SunEye SAVs are reported on a monthly basis by the tool’s report-generation software, and it is common for users to estimate the performance impact of partial array shading by applying these monthly values simply as multiplicative loss factors to unshaded performance predictions. The accuracy of this approach will be addressed later in this work.

**ELECTRICAL IMPACT OF PARTIAL SHADING**

A full, detailed shading simulation tool, developed at University of Colorado-Boulder and NREL, can accurately model arbitrary cell-level shading on PV arrays. This tool has been validated and used to generate system-level predictions of performance loss from partial shade [8]. Although this type of tool, combined with precise shadow mapping, would give the most accurate performance prediction for partially shaded PV arrays, the complexity and runtime make it impractical to use with standard PV modelling software like SAM. Instead, two simplified electrical shade loss models are implemented in SAM and described here: a nonlinear model designed for systems equipped with string and central inverters and a linear model for use with DMPPT systems.

**Shade model for central/string inverters**

**Database creation.**

SYSTEM ADVISOR MODEL uses a database of precomputed loss percentages for different shading scenarios [31] to evaluate the performance of partially shaded PV systems with central or string inverters. The computations use the detailed model mentioned in the preceding texts [8] which simulates the $I$–$V$ behaviour of PV generators’ performance by using a five-parameter single diode model shown in Eqn (3) [32]. In this equation, $I$ and $V$ are the PV generator current and voltage respectively. $I_s$ is the PV generator’s light-generated current, $I_0$ is the dark current, $a$ is the modified ideality factor, and $R_s$ and $R_{sh}$ are the series and shunt resistance.
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The database is created by using datasheet parameters from Trina polycrystalline module TSM-PA05, chosen because it has performance characteristics typical of multicrystalline silicon modules used in residential PV arrays. The database has the following considerations:

- Systems may have up to eight parallel strings, connected to a single central inverter. Any string length and module orientation is allowed, as long as it is uniform across each system.
- Each string can be shaded in 10% increments, from 0 to 100%, independent of each other string. The database is coded by the fraction of modules/submodules shaded in each string.
- The fraction of irradiance available while the module is partially shaded (diffuse fraction) ranges from 10 to 100% of the total plane-of-array irradiance, again in increments of 10%. At any given time, the shaded portions of the PV array receive the full diffuse irradiance, while the unshaded portions receive the full plane of array irradiance.

Partial shading scenario entries are stored for each combination of number of strings, fractional string shading, and available shaded diffuse fraction of light. The entries consist of the global and local maximum voltages and currents, scaled relative to the unshaded case. Because the database is indexed by the maximum fraction of any shaded string for each scenario, the voltage and current entries can be stored in a diagonal matrix of values, which minimises the size of the database. When there are ns possible values for string shade extent and nd possible values for the diffuse fraction of irradiance, the number of entries is required to address a PV system with NumStrings strings given in Eqn (4).

\[
\text{Database Entries} = \sum_{N=1}^{\text{NumStrings}} nd \left( \frac{(ns-1+N)!}{(ns-1)!} - 1 \right)
\]  

In the case of our database, \(ns = 11\) and \(nd = 10\), so for \(\text{NumStrings} = 8\), the total number of entries is 755 730. When the database is compressed, its size is <3 MB, and in RAM, it is <12 MB. These sizes are reasonable to use with PV modelling software such as SAM.

If for some reason the system is unable to operate within the range of a scenario’s stored power points (for instance, if the maximum power point voltages are outside of the maximum power point tracking range of the inverter), then the database indicates that no power is produced. This may compromise the accuracy of the performance prediction for some PV systems that are not optimally sized or configured.

**Database access.**

Database access requires basic information about the PV system to be simulated, including module and inverter characteristics, array configuration, unshaded and shaded plane-of-array irradiance and PV cell temperature, and the shaded fraction of each string of modules. All but the last item of this information are readily available to the user in array design documents, weather files, or datasheets. Per-string shading must be determined by using a tool that maps shade patterns onto the plane of the PV array, such as the 3D shade calculator currently implemented in SAM [35] or other third-party CAD software.

During each database access, the per-string shading and shaded (diffuse) irradiance fractions are rounded to their nearest tenth, and these values are used to obtain the most relevant set of direct current (DC) and voltage system operation from the database. The maximum power output is calculated, within the PV system’s inverter MPPT voltage range, and this is then used to compute the partial shading losses. Database access time for a year of hourly points requires about 1 s, which meets the goal of a very fast simulation time. By comparison sake, two previously published shading models in Refs [30] and [8] would require 1 and 10 min respectively, for comparable annual simulations.

**Database electrical model validation.**

The shade database described in the preceding texts has simplifications to make it practical for use with commercial PV modelling tools. These limitations include rounding levels of shade extent and diffuse irradiance fraction to the nearest tenth and assumptions that shade does not affect module operating temperature. To examine the potential errors introduced by these assumptions, two comparison shade models were chosen to assess annual shade loss calculations: a detailed five-parameter cell-level model [8] and an empirical estimation of string-level MPPs described in Refs [30] and [40]. Potential accuracy advantages of these two models include greater flexibility in system irradiance and temperatures, at the cost of greater computation run time, as described in the preceding texts.

Comparison of the three partial shade models (‘detailed model’, ‘shade database’, and ‘Psarros model’) is conducted via annual energy simulations of the PV system drawn in Figure 3, a southwest-facing rooftop installation with two parallel strings and large trees at a distance. Shading is mapped onto the array at the cell substring (module bypass diode) level. All models have identical inputs for array operating conditions, including irradiance, temperature, and shade extent. On an annual basis, the shade database predicts nearly the same losses attributed to partial shading as the detailed model (Table II) despite its simplifications and the Psarros model [30] comes within 1% of the other two models. Predicted shade loss is further investigated by month in Figure 4. One can see here that the detailed model predicts more loss than the other two models during the more heavily shaded fall and winter months. The shade database also appears to overpredict summer
shade losses for this particular array, which may in part be due to rounding errors of shade extent.

On an annual basis at least, the shade database does a reasonable job predicting the electrical losses caused by partial shading of the PV array. Given its faster runtime and more faithful representation of the full electrical model, as compared to the Psarros model, it may be a preferred solution for practical PV modelling.

**Shade model for distributed power electronics**

Photovoltaic systems with DMPPT, such as those with module-level DC–DC converters or microinverters, experience a performance loss that is approximately linear with respect to the fraction of the array that is shaded [8,22]. As such, the linear shade model simply applies a 1:1 ratio between the extent of shade in a system and the amount of beam irradiance reduction. This is exactly the approach taken in Eqn (1) where diffuse and reflected irradiance is unaffected and incident beam irradiance is reduced by the fraction of the PV array covered in shadow at a given point in time. This treatment would be correct for a PV module in which each cell was equipped with MPPT hardware, but PV modules equipped with module-level or submodule-level electronics still exhibit some nonlinearity if only a portion of the module or submodule is shaded. Under some conditions, it may be more accurate to calculate the shade extent \( S(t) \), not as an area fraction, but rather as a fraction of modules or submodules per array that are affected by shade.

**FIELD VALIDATION**

**Sites**

Table III summarises 46 installations in the Denver and Los Angeles areas, each with 5–12 months of production data reported either on a 5-min or monthly basis, depending on the data source. Concurrent nearby meteorological
Table III. Summary of photovoltaic systems used for validation.

<table>
<thead>
<tr>
<th>Central/string inverter</th>
<th>Microinverter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unshaded</td>
<td>&lt;5% annual predicted loss</td>
</tr>
<tr>
<td>Central/string inverter</td>
<td>4</td>
</tr>
<tr>
<td>Microinverter</td>
<td>2</td>
</tr>
</tbody>
</table>

data for each site are available, collected by NREL’s Measurement and Instrumentation Data Center [41]. In addition to the PV production data, we obtained additional site metadata, such as the array tilt, azimuth, and brand of the PV modules; the type of inverter equipped; and the physical site address. Each partially shaded PV array also has onsite Solmetric SunEye survey data, with monthly SAVs.

Methodology

The PV arrays were simulated in SAM, using the available site metadata. Model loss factors were set to default values except for soiling loss, which was set to 3%, and module mismatch loss, which was set to 1% for systems with central/string inverters, and 0% for systems with distributed power electronics. These are the default values for the widely used PVSYST modelling tool [42]. All of the SAM simulations use appropriate nearby (within 50 km) weather data collected through Measurement and Instrumentation Data Center, adjusted for system downtime indicated by the performance data. The PV systems located in Colorado also use SAM’s snow loss model [43,44].

A shading scene was created for each partially shaded site by using shade obstruction details from aerial imagery found online from Google Earth or Bing Maps, and shading losses were calculated in SAM as described above. The shading scenes were created by using a first-pass estimate of the shade obstructions, independent of the measured data. For comparison’s sake, partially shaded PV arrays were also modelled by using their available SunEye roof survey data instead of the CAD-based shading tool. For these SunEye cases, the arrays were simulated without shading in SAM and the monthly SAVs were used as linear shade loss factors, applied to the modelled unshaded AC production values.

PV FLEET SHADING DATA

On a fleet-wide basis, the relative bias errors for both the shaded and unshaded systems were less than 2.5%, which is a reasonable result, given the many sources of uncertainty, including but not limited to location of the weather stations relative to the arrays, use of default loss values, or array tilt/azimuth/roof clearance ambiguity. It is interesting to consider the data by system type and shading extent, separating the partially shaded systems by inverter type (central vs micro) and shade extent (predicted losses <5% vs ≥5%). Figure 5 shows the distributions of the PV systems’ annual relative bias error, created by using histograms with a smoothing curve fit and normalised to the number of systems in each grouping. The median values for each of the fits are presented in Table IV. One can see that the unshaded systems have a slight negative median bias, due in part to the sources of modelling uncertainty mentioned in the preceding texts. Shaded systems with central inverters show a bit more bias, negative or positive depending on shade extent, than their counterparts with microinverters. However, all system types and shade extent groupings have median annual bias errors within 2.5% when using the SAM tool for performance prediction.

Next, we investigated the monthly cumulative distribution functions of all PV arrays’ energy production with respect to model error, again separating the systems by inverter type. These are shown in Figure 6, with the P(50) and P(10)/P(90) values, calculated by using the method described in Ref. [45], marked and listed in Table V. For both inverter types, the P(50) values are very close to zero, indicating that the central tendency of each shade model is not strongly biased either positive or negative. The cumulative distribution functions also indicate that 80% of the energy is generated with an absolute monthly error of <9% for the central inverter systems and <8% for the microinverter systems. Given the many potential sources of inaccuracy in the SAM simulations, this is very good agreement between the measured and modelled results.

To further evaluate the accuracy of the shading tools in SAM, we calculated the root-mean-square errors, or RMSEs (Equation (5)), for the total energy production on a fleet-wide basis, separating the systems into two groups, shaded and unshaded (Table VI), and further dividing the partially shaded systems by inverter type (Table VII). In the error equation, $E_{\text{Mod}}$ and $E_{\text{Meas}}$ are the modelled and measured energy production respectively, and $n$ is the number of systems, when the errors are calculated on an annual basis, or the number of system-months of measured data, when errors are calculated on a monthly basis.

$$
\text{Relative Root Mean Square Error} = \sqrt{ \frac{ \sum_{i=1}^{n} (E_{\text{Mod},i} - E_{\text{Meas},i})^2 }{ n } } \times 100\% \quad (5)
$$

The first entry in Table VI shows the annual system
energy production RMSE across all 46 PV systems in this study, and it indicates that the annual RMSEs for the unshaded and shaded systems are both the same at 4.0%. This is not to say that the shading model introduces no additional model uncertainty. Rather, on an annual basis, these additional monthly errors appear to cancel, such that the annual system energy estimation across the fleet was not impacted.

This effect is further illuminated by examining the RMSEs on a monthly basis, with the months of April–September grouped seasonally into ‘summer’ and October–March into ‘winter’. This designation was made so that the typically more shaded winter months would be considered together. As shown in the right half of Table VI, the RMSEs increase slightly for unshaded systems when calculated from monthly data and more considerably for shaded systems. Further, while the seasonal RMSE values are similar for unshaded systems, the partially shaded systems show increased model error in the winter, when shade extent is greater. This may indicate that the shaded systems’ results exhibit some error cancellation on an annual timescale and that the shade model errors increase in the winter months. Using the root-sum-square to determine uncertainty, one can infer that, for this fleet, the shade model contributed an additional RMSE of 3.6% ($6.6^2 = 5.5^2 + 3.6^2$) for summer energy production and 8.3% for winter energy production. Table VII also considers the difference in monthly model accuracy for central inverter and microinverter systems and shows that the monthly RMSEs are higher for shaded systems with central inverters than microinverters. This is expected as the model for central inverters is more complicated and

Figure 5. Distributions of annual bias error for (top) central inverter systems and (bottom) microinverter systems. Low shade systems are those with an estimated loss of less than 5% due to partial shading, and high shade systems are those with estimated shading losses of 5% or more. Zero shade systems include both central inverter and microinverter systems. [Colour figure can be viewed at wileyonlinelibrary.com]
Figure 6. Cumulative distribution functions of the photovoltaic (PV) systems’ energy production with respect to SAM model bias error. The (top) central inverter and (bottom) microinverter distributions include the monthly model errors for each PV system of that type. [Colour figure can be viewed at wileyonlinelibrary.com]

Table V. Per cent error probabilities from the cumulative distribution functions of energy production.

<table>
<thead>
<tr>
<th></th>
<th>P(50)</th>
<th>P(10)</th>
<th>P(90)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central inverter</td>
<td>–0.9</td>
<td>–8.6</td>
<td>7.4</td>
</tr>
<tr>
<td>Microinverter</td>
<td>–0.5</td>
<td>–7.6</td>
<td>7.2</td>
</tr>
</tbody>
</table>

Table VI. Per cent root-mean-square errors for shaded and unshaded systems’ annual and monthly data.

<table>
<thead>
<tr>
<th></th>
<th>Annual</th>
<th>Summer</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unshaded</td>
<td>4.0</td>
<td>5.5</td>
<td>5.7</td>
</tr>
<tr>
<td>Shaded</td>
<td>4.0</td>
<td>6.6</td>
<td>10.1</td>
</tr>
</tbody>
</table>

Table VII. Per cent root-mean-square errors for shaded systems’ monthly data by inverter type and season.

<table>
<thead>
<tr>
<th></th>
<th>Summer</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central inverter</td>
<td>7.2</td>
<td>12.0</td>
</tr>
<tr>
<td>Microinverter</td>
<td>5.8</td>
<td>8.3</td>
</tr>
</tbody>
</table>

Figure 7. Distributions of annual bias error for (top) central inverter systems and (bottom) microinverter systems, comparing the results of using the SAM 3D computer-aided design (CAD) models and SunEye rooftop surveys. Low shade systems are those with an estimated partial shading loss <5%, and high shade systems have ≥5% shade loss. [Colour figure can be viewed at wileyonlinelibrary.com]
sensitive to model or CAD placement errors as described above.

Finally, Figure 7 and the associated Table VIII compare the accuracy of the SAM 3D shading models to that of energy predictions made by using SunEye rooftop site surveys. As previously mentioned, the SunEye results are calculated by applying the rooftop surveys’ monthly SAVs as linear power losses to the unshaded AC energy production predicted by SAM. While the results of the two tools are similar under high shade conditions for systems with microinverters (median errors are within 1% of one another), the SAM shade model has more accurate and consistent results for the other three shading categories. These results suggest that, while a rooftop site survey is a good tool for shade modelling, accuracy is not compromised by instead using CAD-based models aided by aerial imagery.

**CONCLUSIONS**

We gathered high-quality energy production data for 46 residential PV systems, with associated annual shading losses between 0% and 20%. Using array details such as location, size, orientation, and inverter type, we simulated each of these systems in NREL’s SAM tool, employing its 3D CAD-based calculator to map shadows onto the arrays. We describe a method for calculation of the resulting performance losses, including a linear model for systems equipped with microinverters and a nonlinear model for central inverter systems. These methods are benchmarked against existing methods and integrated into the SAM simulation tool. When comparing the estimated with the measured production data, the median annual bias errors were 2.5% or lower in all cases.

The RMSE on an annual basis was 4% for both shaded and unshaded systems, indicating that, in aggregate, the partial shading model does not appreciably increase uncertainty in annual energy predictions. When the RMSE was calculated on a monthly basis, the shading model exhibited greater uncertainty—accounting for a 4%–9% increase depending on the season. The partial-shading model developed for PV systems with central inverters was found to have greater uncertainty than the linear microinverter model, owing in part to the greater complexity of the nonlinear model.

We also compared the results of the 3D CAD-based models to those obtained by using the Solmetric SunEye rooftop site surveys for each system and found the 3D CAD method to have comparable or better accuracy, given accurate placement of shade obstructions. This effort is novel in that it was the first time that multiple shading tools were compared to production data from a fleet of PV systems on an annual basis and the contribution of shade loss to modelling uncertainty was quantified. The results indicate that accurate modelling of PV system shade can be done remotely without access to the rooftop of a given property. The models described here are also shown to be sufficiently accurate to have little impact on model uncertainty on an annual basis across multiple installations.

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A fleet of shaded photovoltaic systems with string and module-level inverters

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Diffuse irradiance loss from nearby or horizon obstructions is due to the reduced field of view of the solar collector to the open sky dome. Many irradiance models exist that calculate the translation of horizontal diffuse irradiance to a tilted plane. Here, an isotropic diffuse model is assumed which results in diffuse irradiance loss that is a constant independent of solar position. The output value here is an additional diffuse shading loss fraction that can be applied onto the diffuse irradiance of whichever tilted plane model is selected.

Conceptually, a 2D integral is solved in the (θ, φ) space where θ is zenith angle from vertical and φ is azimuth angle from north. Additionally, a two-axis rotation is required to define zenith angle θ in the reference plane of the tilted, rotated PV array. This angle is calculated for tilt angle β and azimuth orientation γ as [46]

$$\theta = \cos^{-1}(\cos\theta \cos\beta + \cos\gamma \sin\beta \sin\theta + \sin\theta \sin\beta \sin\gamma)$$

(1)

Additionally, the projection of the PV array for a given (β, γ) in the (θ, φ) coordinates is required. This is accomplished by solving \( \cos \theta = 0 \), which defines the \( \theta_{\text{plane}} \) coordinates behind the plane of the PV array:

$$\theta_{\text{plane}} = \arctan2\left( \frac{-\cos(\gamma - \phi) \sin \theta}{\sqrt{(\cos^2 \beta + \cos^2 \gamma - \phi \sin^2 \beta)}} , \frac{\cos \theta}{\sqrt{(\cos^2 \beta + \cos^2 \gamma - \phi \sin^2 \beta)}} \right)$$

(2)

where \( \arctan2 \) is a four-quadrant arctangent of \((y/x)\) where the first argument of \( \arctan2 \) is the \( y \) denominator and the second argument is the \( x \) numerator.

Given these equations, diffuse irradiance is integrated for both the unshaded view of the sky and for the diffuse shading loss attributed to obstructions above the horizon. The unshaded integral considers only the portion of the sky above the horizon (\( \theta < 90^\circ \)) and above the view of the array plane \( \theta_{\text{plane}} \). This is represented in Figure A1 in the succeeding texts as the integral of open sky area above the blue array plane:

$$G_{\text{d, unshaded}} = \int_{\phi=0}^{360} \int_{\theta=0}^{\theta_{\text{plane}}} \cos \theta \sin \theta \, d\theta \, d\phi$$

(3)

The shaded integral considers the portion of the sky that is both visible to the array plane yet also obstructed by shading objects (\( \theta_{\text{Obs}} \)). This is represented in Figure 8 in the succeeding texts as the integral below the red horizon obstructions and above the blue array plane.

$$G_{\text{d, shaded}} = \int_{\phi=0}^{360} \int_{\theta=0}^{\theta_{\text{Obs}}} \cos \theta \sin \theta \, d\theta \, d\phi$$

(4)

The weighting factor \( \cos \theta \sin \theta \, d\theta \) in the diffuse integrals in the preceding texts includes a spherical integral weighting factor \( \sin^2 \theta \, d\theta \) times the cosine incidence angle loss relative to the PV array normal \( \cos \theta \). Note that \( \theta \) is only defined from \( 0 < \theta < 90^\circ \) in the weighting factor mentioned in the preceding texts.

The overall fraction of diffuse irradiance lost to horizon shade is \( G_{\text{d, loss}, \text{ horizon}} = G_{\text{d, shaded}} / G_{\text{d, unshaded}} \). This loss term varies throughout the array because the obstruction zenith angle \( \theta_{\text{Obs}} \) depends on the position within the array. Strictly speaking, \( G_{\text{d, loss}, \text{ horizon}} \) should be tabulated separately for each PV module in the array. However, variation within the array tends to be small and unlikely to introduce additional mismatch losses. Therefore, in the SAM approach, \( G_{\text{d, loss}, \text{ horizon}} \) is averaged across the array and applied as a single diffuse loss fraction.
**Figure A1.** Example of horizon obstruction and definition of the photovoltaic (PV) array plane in elevation-azimuth coordinates for $\beta = 45$. The unshaded integral in Eqn (3) is taken over the entire sky dome visible to the array, excluding the area behind the plane (blue). The shaded integral in Eqn (4) is included over the area below the horizon obstruction (red). Note that the area below the horizon represents the diffuse loss of a tilted plane relative to horizontal (grey) and is typically handled by a separate transposition model.

[Colour figure can be viewed at wileyonlinelibrary.com]