Impact of input error on PV system simulation under partial shading conditions

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Evaluating the impact of near shading on PV systems is a complex and critical step in the PV design process, dependent on a range of factors including the sun's path in the sky, the nature of the shading object and system topology. Despite record levels of uptake in Australia, consumers have traditionally been discouraged from installing solar systems with unavoidable near shading due to potentially disproportionate power losses (Gairola, et al., 2020). Analysis of systems within the PVOutput.org database in 2016 indicated that 75% of systems were reported to be unshaded (Haghdadi, et al., 2016). Yet the falling cost of PV and improvements in technology suggest that well-designed, partially shaded systems will likely play a key role in actualising the projected additional ~54 GW of untapped, distributed solar capacity in the National Electricity Market by 2050 forecast in the Australian Energy Market Operator's 2022 *Integrated System Plan* (AEMO, 2022).

Modelling approaches in literature demonstrate that there is generally a compromise between model simplicity and model accuracy due to the complexity of partial shading (Saint-Drenan & Barbier, 2019). Furthermore, consumers often lack detailed system information and access to sophisticated tools to accurately describe shading obstructions. Indeed, system tilt and orientation are not typically collected by utilities, relying instead on self-reporting by installers or system owners. Analysis of self-reported information of tilt and orientation of 5000 Australian systems on PVOutput.org in 2017 found that about 10% of systems did not report the tilt angle of PV array and another 32% have reported the wrong value (Haghdadi, et al., 2017).

At present, there remains limited understanding of how to best mitigate the impact of error in input information on simulated PV output, particularly for partially shaded systems. This gap in the literature highlights a need for investigation into assumptions and user input design measures which can best mitigate output error in the absence of detailed system information. Further, an improved understanding of the nature of shading impacts would help inform system design to manage partial shading and ultimately financial decision making for consumers who would otherwise be locked out of the benefits of solar. This two-stage study presents a detailed investigation into the sensitivity of simulated PV output to accuracy of inputs for small-scale residential PV systems modelled in NREL's System Advisor Model (SAM). The first stage of the study investigates the impact of error in measurement of system orientation and tilt angles on simulated output for unshaded systems. The second stage conducts error testing in shading object description of selected systems using SAM's inbuilt 3D shade calculator.

Study 1: Sensitivity to system description

To test sensitivity to error in system tilt and orientation, a 6.4 kWDC unshaded residential PV system was modelled using PVWatts default assumptions. Systems were modelled at 7 baseline orientations and 4 baseline roof tilts based on common construction types found in the housing stock[1]. Each orientation and tilt combination was simulated in 16 locations across Australia using ERMY weather files (Exemplary Energy Partners, 2022) , generating 448 scenarios in total. Error in orientation from ±7.5º to ±22.5º and error in tilt in ±4º increments up to ±12º were introduced, to

[1] There are no fixed standards for roof slope in Australia beyond minimum slopes to ensure drainage. South facing systems were not modelled. Note also that the PV modules were assumed to lie flush with the roof, so the module tilt equals the roof slope and there is no self-shading.

represent potential estimation error. A default residential load profile and time of use (ToU) tariff structure were then applied within SAM to determine the impacts of input error on the annual yield and payback period for each scenario. Table 1 below provides sample summary results for Sydney, showing the percentage absolute error in annual yield for errors of ± 22º in orientation and ±12% in slope for each baseline scenario.

Table 1. Maximum absolute error in annual yield for Sydney

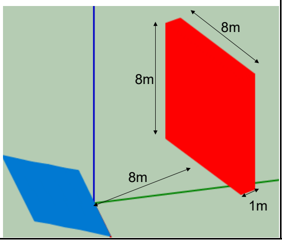
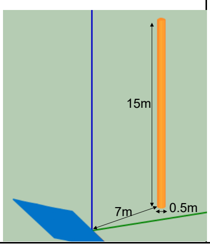
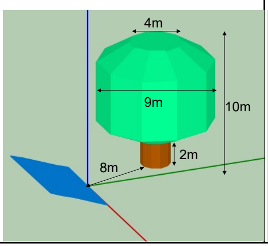
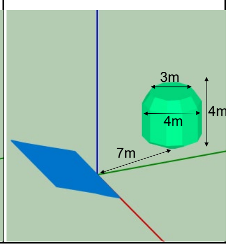
		Baseline roof tilt and error tested			
		Near flat	Skillion	Traditional	Steep
Baseline orientation and error tested		5º ± 12º	15º ± 12º	25º ± 12º	35º ± 12º
N	0º ± 22.5º	6.59%	6.76%	5.33%	8.97%
NE	45º ± 22.5º	5.55%	7.70%	11.67%	15.14%
E	90º ± 22.5º	9.80%	14.49%	18.76%	22.54%
SE	135º ± 22.5º	13.69%	18.85%	23.89%	28.22%
SW	225º ± 22.5º	12.25%	18.81%	24.78%	29.60%
W	270º ± 22.5º	5.10%	10.88%	15.43%	19.11%
NW	315º ± 22.5º	6.75%	6.46%	7.41%	10.84%

It can be seen that south-east and south-west facing systems demonstrate heightened error relative to north-oriented systems. This error is greatest for a steep roof (35º), with maximum error of almost 30% of system output, almost double that for a near flat roof (5º) at the same orientation. These errors were further amplified in evaluation of the payback period, resulting in maximum error of up to 70% for steep, south facing systems. Conversely, the lowest errors on average are achieved by north-facing systems, which tend to have a higher resilience to design flaws (such as system tilt), and hence higher resilience to error in model inputs. West facing systems are found to be marginally more resilient to input error than east facing systems, and have a higher overall annual yield by 9%, on average. These patterns of relative error were found to be consistent across all modelled locations across Australia despite large variations in solar insolation. The percentage error in system output was found to be consistent across all climate zones, while error in payback period is approximately 10% higher for cool temperate zones (i.e. Hobart) compared to tropical zones (i.e. Darwin).

Study 2: Sensitivity to shading object description

Sensitivity to error in shading object description was modelled with SAM's detailed residential PV model and inbuilt 3D shading tool which uses a 'look-up' style shading matrix of pre-computed shading factors to estimate the loss in annual yield (MacAlpine, et al., 2017). A 6.2 kWDC, north facing PV system at 25º tilt was chosen for modelling with 5 horizontal strings of 8 modules assumed to be mounted on a roof. Four shading objects were designed in SAM's CAD-based shading tool to represent common shading obstructions, each modelled at 9 equidistant locations from the base of the array in the north of the sky. Table 2 below depicts object specifications and average simulated annual yield reduction across each of the 9 object locations.

Table 2. Baseline shading object specifications and average reduction in annual yield

<table>
<tr><th></th><th>Block (building)</th><th>Cylinder (pole)</th><th>Large tree</th><th>Small tree</th></tr>
<tr><td>Average reduction In annual yield (%)</td><td>11.76%</td><td>2.47%</td><td>23.92%</td><td>4.47%</td></tr>
<tr><td>Diagram</td><td>
</td><td>
</td><td>
</td><td>
</td></tr>
</table>

For each object orientation and configuration, ±20% error was introduced to the object height and distance from the base of the array[2]. Results are shown in Figures 1 and 2, respectively, with each of the 9 object orientations shown from the point of reference of the active surface on the horizontal axis (North = 0 degrees).

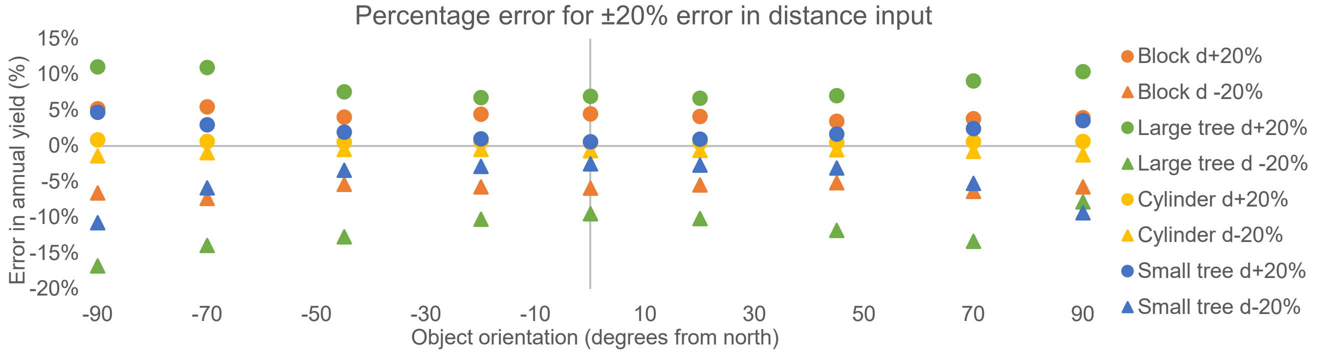


Figure 1. Error in annual yield for ±20% error in object distance from base of array

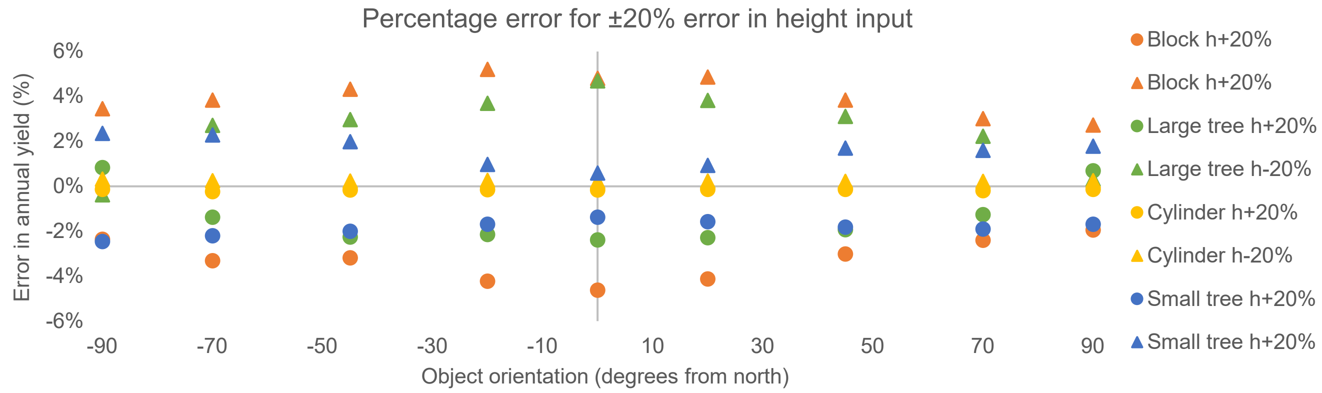


Figure 2. Error in annual yield for ±20% error in object height above base of array

In general, the impact of input error is highest for objects with the greatest shading impact (Table 2). On average, the absolute error in simulated annual yield resulting from ±20% error in measured distance from the base of the array is 4.91%, which is significantly higher than that caused by similar error in height (1.93%). This is particularly true when the distance is *under*estimated, resulting an average error of -5.89% compared to 3.92% increase when overestimated by the same amount for all shading objects. The large tree is the most sensitive to error in distance input, while the block is the most sensitive to error in height input. This may be because the large tree contains a trunk which also changes height proportionally by ±20%, controlling the amount of light to filter beneath the crown and partially offsetting error in annual yield. This observation highlights the crude simplification of trees as shading objects which are diverse and complex by nature yet are reduced in this study to the sum of several opaque polygons (MacAlpine, et al., 2017).

For error in distance, results are most sensitive when the shading object is in the east or west of the sky (object orientation ±90º). This is because the sun's angle in the sky is generally lower during morning and evening, when a small error in distance from the base of the array can result in disproportionate shadows and consequent reduction in output. The opposite appears to be true for error in height, where large objects in the north of the sky (large tree and block) are most sensitive to error since relatively small changes in height can block a larger amount of radiation. However, smaller objects (small tree and cylinder) exhibit the inverse pattern, indicating that there is a lower

[2] Error in cylinder radius, system tilt and orientation were also modelled under partial shading conditions, however the resulting error was found to be insignificant compared to the same input error in height and distance shown here.

threshold for object size where the sun's angle in the north of the sky becomes sufficiently high to avoid major changes to annual yield when height error is introduced. It is acknowledged that the conclusions which can be drawn from this work are limited by SAM's shade-table methodology and CAD-based shading tool which is limited in its ability to define complex shading scenes. Further work is required to validate the conclusions in this study by performing similar tests in other PV simulation software (such as those which use high resolution graphical processing units to describe shading scenes) and by comparing results to experimental data.

Synthesis and conclusion

The combined results demonstrate that simulated PV output is appreciably sensitive to the accuracy of inputs, though the degree to which error is amplified depends on key system characteristics. Systems most vulnerable to heightened error in simulated annual yield include south facing systems with steep tilt and significant near shading, with the most dramatic errors emerging from inaccurate description of the shading object. In all cases, the error was inflated to almost double in the calculation of payback period, potentially leading to sub-optimal system design and misinformed financial decision making. This points to a tangible risk of missed opportunity for prospective system owners, together with the broader benefit of environmental risk mitigation which solar affords society. Nonetheless, insights on system profitability would be strengthened by further investigation into the impact of seasonal and regional variations, combined with diverse load profiles against a range of tariff structures.

Ultimately, the results confirm that PV system modelling software should be designed to encourage maximum possible input accuracy to ensure the integrity of simulated output. This could include a caution to the user if the system is particularly vulnerable to error, integrated with educational and/or technical resources to support the user to best estimate model inputs. Other realistic improvements include implementing optimised, low risk assumptions which minimise potential error in the absence of system information. In the case of unavoidable error, assumptions should be made which tend to underestimate yield to avoid potentially detrimental financial decisions. Ultimately, an estimate of confidence in outputs should be offered which reflects the modelled system's unique vulnerability to error.

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