Validation of SunSPOT Shading Methods and the impact on PV generation

Russell Kindler[1,2], Mike Roberts[1,2] and Anna Bruce[1,2]

[1]School of Photovoltaic and Renewable Energy Engineering, University of New South Wales, Sydney 2052, Australia
[2]Centre for Energy & Environmental Markets, University of New South Wales, Sydney 2052, Australia
rkindler@student.unsw.edu.au

The latest Integrated System Plan (AEMO, 2022) models rooftop PV to be contributing 20% of the National Electricity Market's demand by 2050. This scenario sees a 65% increase over current levels of rooftop PV to create 69 GW of capacity. The main driver for this increase is improved technology, affordability combined with increasing electricity prices that facilitate Australian consumers to financially benefit from installing rooftop PV systems. Given building and landscape geometries of residential environments, it is common for rooftop PV systems to experience partial shading and it can be expected that a significant portion of the 65% increase in rooftop PV capacity will include partially shaded systems. A study which analysed 5000 rooftop PV systems Australia wide from PV Output.org's database in 2016 (Haghdadi et al., 2016.) found that 25% of systems experienced varying degrees of partial shading. Shading on a PV system can significantly reduce output and alter generation curves, thereby impacting expected financial benefits. Determining the impact of partial shading on a rooftop PV system is a critical step in the PV design process, complicated by the many contributing factors including the system location, the nature, height and shape of shading object(s) and the system design (panel placement, orientation, tilt, inverter topology and use of other power electronics). Quantifying these impacts is important in determining the financial case for PV deployment and for additional power electronics (such as microinverters or power optimisers) to mitigate the impacts of shading and therefore facilitate financial benefits to be realised by consumers with partially shaded rooftops.

At present there are few consumer-friendly tools which evaluate the impacts of site-specific shading. The Australian Photovoltaic Institute's (APVI) SunSPOT Solar Potential Tool includes two different methods for Australian consumers to determine their rooftops' solar potential. The first method uses locationally available LiDAR data to determine roof slope and shading and calculate the solar insolation incident on a rooftop. In the absence of this LiDAR data, the tool's second method involves users adding and inputting the dimensions of cylinder(s) and/or rectangular prism(s) to approximate nearby building and natural object geometries, to determine the portion of the PV array which is shaded at different sun positions. This is then applied to irradiation data and the impact on PV electrical output is modelled. The two methods SunSPOT uses assist Australian consumers to evaluate the economic benefit of installing a PV system on their roof. A gap in the current literature and absence of alternative consumer modelling tools leads to the need for a study to validate the two SunSPOT methods.

This study presents a comparison of the two SunSPOT shading methods and validation against National Renewable Energy Laboratory's (NREL) System Advisor Model (SAM) detailed model and PV Watts model. The output electrical generation and shading results were compared for multiple rooftops with near shading objects. The reason for the choice of SAM and PV Watts was their high accuracy and reliability proven through extensive validation (MacAlpine and Deline, 2015), (Freeman et al., 2014) and subsequent establishment as an industry benchmark for the detailed modelling of PV systems. It should be noted that an earlier version of SunSPOT was validated using a similar methodology (Copper and Bruce, 2014). This earlier version used more granular slope orientation and shading data compared with the current SunSPOT method and did not include the non-liDAR method.

Methodology:

SunSPOT's Non-LiDAR, SAM and PV Watts models require the dimensions and location (relative to the modelled PV array) of shading objects as inputs. In the absence of real-world data, google earth was used to determine object dimensions to create 3D models of the systems. Google earth uses photogrammetry to determine the elevations of different objects. Various studies have determined that this elevation data is of high accuracy and can be used as a reliable source of data for real world applications (Wang et al., 2017). In comparing the shading values, another limitation arises out the granularity of SunSPOT shading values due to the shading calculator calculating shading values for different sun positions. SAM's shading modelling computes yearly datetime values at user specified frequencies of 1 minute to 60 minutes. To compare the shading results from SunSPOT LiDAR and SunSPOT Non-LiDAR, with SAM, interpolation is required. This interpolation leads to significant error in shading values.

For this abstract, 3 sites from Sydney with different environmental characteristics causing different partial shading patterns were analysed in detail (Figure 1). These sites were chosen since LiDAR and google 3D data was both available.

Figure 1 – Three modelled sites in SunSPOT non-LiDAR: System 1 (LHS), System 2 (Centre) & System 3 (RHS)

Results

For each of these preliminary sites three different statistics (Table 1) were calculated. SunSPOT LiDAR and non-LiDAR methods were highly correlated for all three systems resulting in an average mean bias error of 0.025 and Spearman and Pearson coefficients at 0.994 and 0.968 respectively. SunSPOT non-LiDAR performed marginally better than the LiDAR method with respect to SAM but were both highly correlated. The comparison to PV watts yielded similar Spearman coefficient results indicating a positive linear relationship but also larger mean bias errors and smaller Pearson coefficients indicating a greater significance of outliers.

Table 1 - Generation Correlation Results

System	Metric	SunSPOT LiDAR vs SunSPOT non - LiDAR	SunSPOT LiDAR vs SAM	SunSPOT non - LiDAR vs SAM	SunSPOT LiDAR vs PV_watts	SunSPOT non - LiDAR vs PV_watts
1	Mean Bias Error (kW)	-0.044	0.018	0.062	-0.218	-0.173
	Spearman Coefficient	0.992	0.974	0.977	0.950	0.954
	Pearson Coefficient	0.959	0.862	0.887	0.810	0.834
2	Mean Bias Error (kW)	0.025	0.112	0.086	-0.125	-0.151
	Spearman Coefficient	0.995	0.979	0.981	0.960	0.960
	Pearson Coefficient	0.979	0.886	0.896	0.857	0.852
3	Mean Bias Error (kW)	0.096	0.092	-0.003	-0.187	-0.283
	Spearman Coefficient	0.994	0.945	0.954	0.947	0.955
	Pearson Coefficient	0.966	0.806	0.856	0.751	0.797
Average	Mean Bias Error (kW)	**0.025**	**0.074**	**0.049**	**-0.177**	**-0.202**
	Spearman Coefficient	**0.994**	**0.966**	**0.971**	**0.952**	**0.956**
	Pearson Coefficient	**0.968**	**0.851**	**0.880**	**0.806**	**0.828**

When comparing the shading results, there was less correlation and large mean bias errors. Further work is required in determining the impact of data granularity on this result.

Table 2 - Shading Correlation Results

System	Metric	SunSPOT LiDAR vs SunSPOT non-LiDAR Shading	SunSPOT LiDAR vs SAM Shading	SunSPOT non - LiDAR vs SAM Shading
1	**Mean Bias Error (%)**	3.238	0.135	-3.103
	Spearman Coefficient	0.575	0.616	0.784
	Pearson Coefficient	0.647	0.736	0.782
2	**Mean Bias Error (%)**	-2.435	-3.020	-0.585
	Spearman Coefficient	0.827	0.826	0.856
	Pearson Coefficient	0.823	0.849	0.868
3	**Mean Bias Error (%)**	-1.889	-7.674	-5.786
	Spearman Coefficient	0.761	0.812	0.771
	Pearson Coefficient	0.887	0.807	0.835
Average	**Mean Bias Error (%)**	**-0.362**	**-3.520**	**-3.158**
	Spearman Coefficient	**0.721**	**0.751**	**0.804**
	Pearson Coefficient	**0.786**	**0.797**	**0.828**

To further investigate the impact of discrepancies of shading values on electrical output the daily generation and shade curves where the max Euclidean distance between shading values for SunSPOT LiDAR and SAM and SunSPOT non-LiDAR and SAM occurs was plotted (Figure 2).

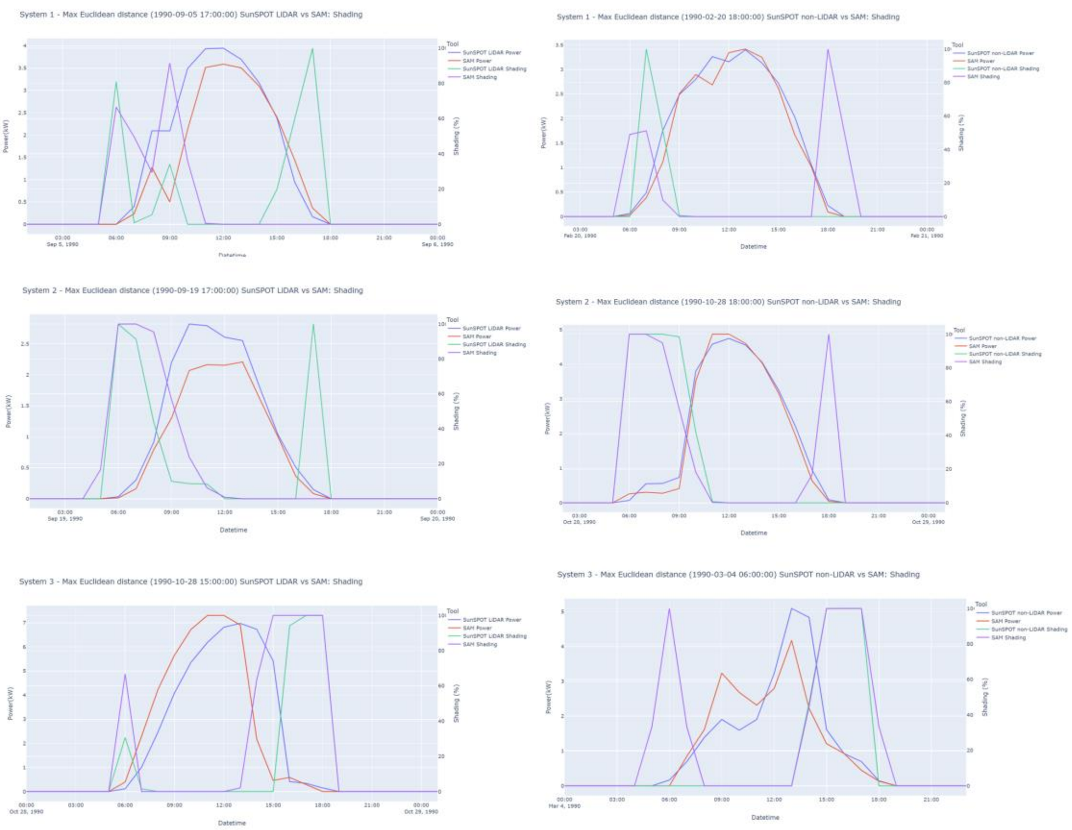

Figure 2 - Max Euclidean Distance Daily Generation vs Time and Shade curves on Secondary axis vs Time

The generation curves are quite closely correlated despite uncorrelated shade values here for all systems. This indicates potential error in the interpolation used in generating comparable shade data. Further investigation is required here.

The annual generations for each site are similar (Figure 3) with an average 7% difference for SAM and non – LiDAR and an average 9% difference for SAM and LiDAR. System 3 has a difference of 0.2%.

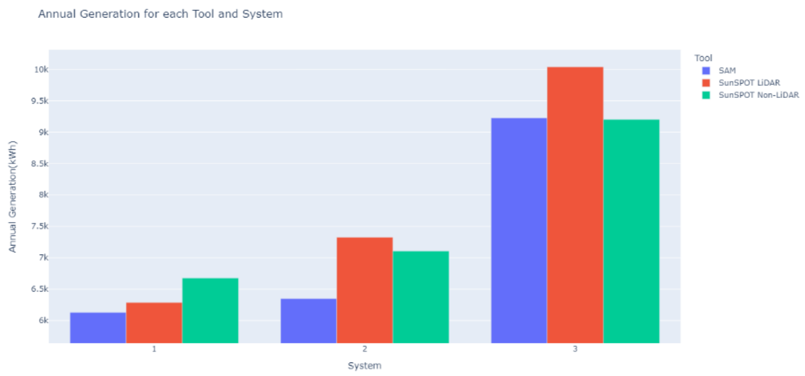

Figure 3 - Annual Generations for each system and tool

Conclusion:

The above preliminary results suggest that there is a high level of correlation between SunSPOT LiDAR, SunSPOT non-LiDAR and SAM modelling generation outputs for partially shaded systems. These results begin to validate the SunSPOT tool's ability to quantify the impacts of partial shading on rooftop PV systems in an easy-to-use consumer-oriented application. Further work is required to analyse a larger sample of systems for the results to be conclusive. Further work is also required to further investigate the impact of shading data granularity on the correlation results for SunSPOT shading values with SAM shading values. Quantifying the impact of these variations on output financial metrics would also contribute to further validate the uses of SunSPOT by Australian consumers to determine the economic case for installing rooftop PV. Ultimately, the SunSPOT tool through both methods performs significantly well further adding to its reputation as an accurate and independent source of information for Australian consumers.

References

AEMO, 2022. 2022 Integrated System Plan, Integrated System Plan. Sydney.

Copper, J., Bruce, A., 2014. Validation of Methods Used in the APVI Solar Potential Tool. https://doi.org/10.13140/RG.2.1.2040.5925

Freeman, J., Whitmore, J., Blair, N., Dobos, A.P., 2014. Validation of Multiple Tools for Flat Plate Photovoltaic Modeling Against Measured Data. Renewable Energy.

Haghdadi, N., Copper, J., Bruce, A., MacGill, I., 2016. Operational performance analysis of distributed PV systems in Australia.

MacAlpine, S., Deline, C., 2015. Simplified method for modeling the impact of arbitrary partial shading conditions on PV array performance, in: 2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC). Presented at the 2015 IEEE 42nd Photovoltaic Specialists Conference (PVSC), IEEE, New Orleans, LA, pp. 1–6. https://doi.org/10.1109/PVSC.2015.7355938

Wang, Yinsong, Zou, Y., Henrickson, K., Wang, Yinhai, Tang, J., Park, B.-J., 2017. Google Earth elevation data extraction and accuracy assessment for transportation applications. PLoS One 12, e0175756. https://doi.org/10.1371/journal.pone.0175756