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Calculation of PV System Degradation Rates in a Hot Dry Climate

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Abstract

This study quantifies the AC power degradation rates (%/year) of a subset of the PV systems located at the Desert Knowledge Australia Solar Centre (DKASC). The analytical techniques of linear regression (LR) and classical seasonal decomposition (CSD) were utilised in conjunction with the metrics of Performance Ratio (PR) and Weather Corrected Performance Ratio (WCPR) to explore the effect of methodology on calculated degradation rates. In addition, three sources of input irradiance data were also explored. The results indicate that both the choice of methodology and irradiance input had a notable impact on the calculated degradation rates. In particular, this study found the calculated degradation rates decreased by ~0.2% (absolute); when onsite measured irradiance was replaced with the higher quality irradiance data source measured nearby at the Alice Springs airport (~5km away) by the Australian Bureau of Meteorology (BoM). Importantly, this study determined that degradation rates cannot be calculated via the use of the BoM satellite derived irradiance dataset, which is available in a 5x5km grid across the entire Australian mainland, due to inconsistent bias in the dataset over time.

For the combined WCPR-LR method, the mean and median annual degradation rates of the 16 systems analysed were 0.81% and 0.75% respectively, varying between 0.28%/year and 1.49%/year. For the mono/polycrystalline PV systems (12 of the 16 systems analysed) the mean and median degradation rates decreased to 0.68% and 0.69% respectively. This collection of degradation rates fall within the mean and median system level degradation rates reported within the literature for x-Si technologies (mean = 0.69%-0.81%, median = 0.61%-0.69%) (Jordan et al. 2016)). The results from this study also showed that the single roof mounted PV system at DKASC has been degrading at a faster rate than the same module technology in a rack mounted configuration.

1. Introduction

Quantifying the long term performance of photovoltaic (PV) systems is essential for accurately predicting the energy delivery and economic viability of PV systems over their lifespans. The metric commonly utilised to quantify output power decline of PV modules and systems over time is known as the degradation rate. In their compendium of PV degradation rates, (Jordan et al. 2016) report median system level degradation rates for x-Si PV technologies in the range of 0.61-0.69%/year with mean values of 0.69-0.81%/year. The reported module level degradation rates for x-Si were median values in the 0.4-0.67% range and mean values in the range of 0.51-0.91%/year.

The compendium reported that the amount of published data on PV degradation rates has increased in recent years, with more than 11000 degradation rates reported in almost 200

studies from 40 different countries. Of these 200 studies, only 2 studies from Australia were located (Muirhead et al. 1995, Hawkins et al. 1996), dating back to modules installed in the 1980s. Based on the studies reviewed and referenced in the compendium (Jordan et al. 2016), no studies of degradation rates have been reported in the past two decades for PV systems in Australia. Hence recent Australian studies into the long term performance of PV systems can provide invaluable information for improving predictions of PV power and economic viability in the Australia context.

Importantly, the Jordan et al. compendium indicates that degradation rates and their mechanisms may also be impacted by hotter climates and mounting configurations that lead to sustained higher temperatures (Jordan et al. 2012, Jordan et al. 2016). In addition, the compendium indicates that the statistical procedures employed, including (but not limited to) methodology and sampling can also influence the determined degradation rate. Similarly, (Phinikarides et al. 2015) review of PV degradation rate methodologies showed that the determined degradation rate was not only technology and site dependent but was also methodology dependent.

2. Methodology

(Phinikarides et al. 2015) review into PV degradation rate methodologies identified four primary statistical analysis methods and four general categories of performance metrics. These methods and metric categories are listed in Table 1.

Table 1: Typical methods and metrics used in degradation rate analyses

Statistical Methods	Performance Metrics
Linear Regression (LR)	Electrical parameters from IV curves – indoor or outdoor conditions and corrected to STC.
Classical Seasonal Decomposition (CSD)	Regression models: Photovoltaic for Utility Scale Application (PVUSA) and Sandia models
Auto Regressive Integrated Moving Average (ARIMA)	Normalised ratings: Performance ratio (PR), Weather Corrected Performance Ratio (WCPR) and P_{MPP}/G
Locally Weighted Scatterplot Smoothing (LOESS)	Scaled ratings: P_{MPP}/P_{max}, P_{AC}/P_{max} and kWh/kW_p.

(Phinikarides et al. 2015) indicated that that the IV method with degradation rates calculated by the percentage error (PE) between two consecutive temporal ratings produced the lowest degradation rates. The linear regression method was found to produce results with considerable variations and uncertainty. The CSD method produced the highest degradation rates for mono and multi crystalline silicon technologies, but with lower uncertainty than the LR method. Whilst the ARIMA and LOESS methods, albeit less popular, produced results with low variation and uncertainty and with good agreement across the two metrics.

The review also indicated that a minimum testing period of 3-5 years was found to be necessary in order to obtain accurate measurements of the degradation rate from field measurements. In other words, the uncertainty of the statistical method employed declined with increasing observation time, as random variations and seasonality have a smaller impact on the underlying trend (Phinikarides et al. 2015).

Finally, the statistical methods that can be employed to calculate degradation rates are dependent on the data available. For instance in this study IV measurements are not available, hence calculation of degradation rates with the IV performance metric are not possible.

The work presented in this study aims to quantify the AC power degradation rates of PV systems located within the hot dry climate of Alice Springs (NT). Further, this paper investigates the impact of methodology choice by comparing degradation rates calculated via two performance metrics, PR and WCPR, the two statistical methods of linear regression and classical seasonal decomposition and three sources of input irradiance data. Analysis of the degradation rates via the ARIMA and LOESS methods are not presented within this paper, but will be investigated in future planned work.

2.1. Performance Metrics – Performance Ratio and Weather Corrected Performance Ratio

The Performance Ratio (PR) is a metric, defined in IEC 61724, which measures the overall effect of losses on a PV system by comparing the ratio of the PV system output with the output from an ideal system in the same array plane, but with no losses due to temperature, incomplete utilisation of irradiance, system component inefficiencies or failures (IEC 1998). The Weather Corrected Performance Ratio (WCPR) is a variant of the PR which corrects for the losses due to temperature. The equations for the two metrics are,

$$PR = \frac{\sum_i P_{AC}}{\sum_i \left[P_{STC} \cdot \frac{POA}{1000}\right]}, \qquad WCPR = \frac{\sum_i P_{AC}}{\sum_i \left[P_{STC} \cdot \frac{POA}{1000} \cdot \left(1+\gamma\left(T_{c-1}-T_{c-avg}\right)\right)\right]}$$

where P_{AC} is the measured AC electrical generation (kW), P_{STC} is the rated power of the array under standard test conditions, γ is the temperature coefficient of the array maximum power, $T_{c\text{-}i}$ is the cell temperature at a given point in time (i) and $T_{c\text{-}avg}$ is the average cell temperature of the array over the period of data analysed.

PV cell temperature in this study was calculated using the Sandia module and cell temperature models (King et al. 2004), with options: module type = Glass/cell/polymer sheet and mount = open rack. The average cell temperature was calculated using the POA weighted average cell temperature method as presented in (Dierauf et al. 2013).

2.2. Statistical Methods – Linear Regression and Classical Seasonal Decomposition

The statistical method of linear regression, simply applies ordinary least squares (OLS) to determine a linear line of best fit to the data series of interest. The degradation rate is then simply the slope of the line of best fit. The statistical model assumed in OLS is of the form $y = mx + b$ where y represents the modelled or fitted values and m and b are the variables being solved for. m and b are ultimately determined by minimising the sum of squared residuals between the fitted line and the dataset.

Classical Seasonal Decomposition (CSD) works on the concept that the long term trend of a data series consist of the 3 components of trend, seasonality and the residual. For PV performance analysis, the trend can generally be extracted by applying a 12 month moving average on the data series. Standard linear regression can then be applied to the trend line to calculate the degradation rate. The "seasonal_decompose" function within Python's Statsmodels package was utilised to undertake CSD in this study, an example of which is presented in Figure 1 for the system labelled "3 BP Solar" at the DKASC.

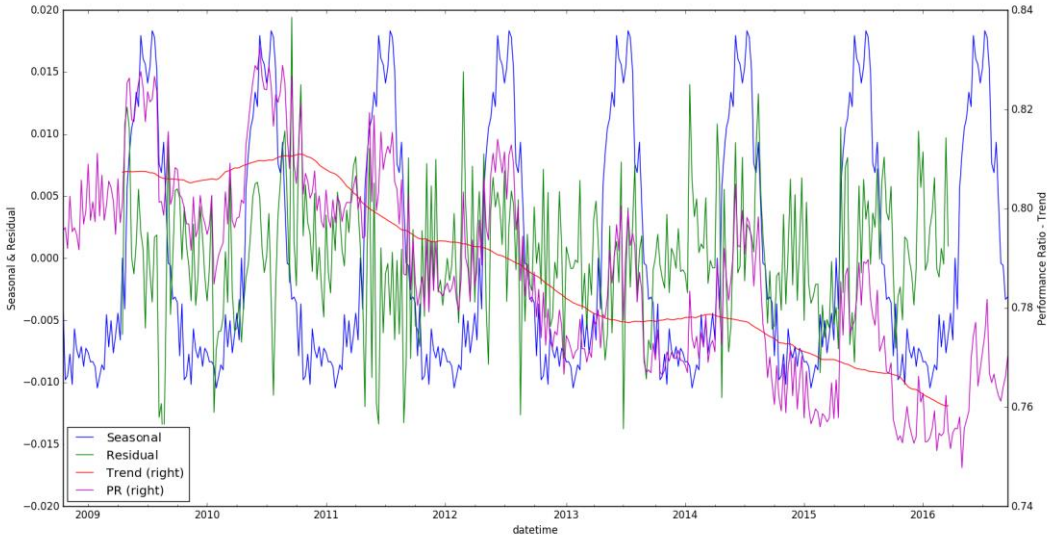

Figure 1: Seasonal decomposition of the Weekly PR for system '3 BP Solar'

2.3. Data Filtering

(Jordan et al. 2014) highlighted that a combination of binning, data filtering and assessing data from the same time period each year has been shown to reduce degradation rate uncertainty. However, it was also highlighted that the filtering process may not only affect the uncertainty but the calculated degradation rate itself. This study has applied the "Elements of a Standard Method" outlined within the study by (Jordan et al. 2014) with a few caveats. The general methodology utilised in this study was:

2.3.1. Data integrity

1. Time shifts – Time shifts observed within the data sets were corrected for. Time shifts were determined by visually inspecting the time series data in comparison to weather data from the BoM. Time shifts were also observed by comparing data from one year to the next.
2. Missing data was flagged and excluded from the analysis.

2.3.2. Data Cleaning:

1. Stability filter – Used to reduce noise caused by variable days. Two stability filters were applied in this analysis, POA irradiance and a module temperature filter. The filters were applied by calculating the difference between consecutive time stamps then excluding any data points which exceeded the standard deviation calculated from the distributions of the absolute difference. The limits were defined as $\mu \pm \sigma$ of the absolute differences.
2. POA Irradiance filter – Used to reduce the uncertainty of the calculated degradation rate, by applying an upper and lower boundary of the irradiance data which can be used in the analysis. The POA irradiance limits were determined by a visual analysis of the dataset and were set at 600 and 1200 W/m^2 respectively.
3. Fixed Outlier filter – Used to reduce the effect of un-documented maintenance events or shading. The fixed outlier filter in this study was applied via fixed PR/WCPR limits. (Jordan et al. 2014) suggested the ratio of power production over irradiance as a metric for

the outlier filter. Such a metric is essentially a calculation of the PR. The upper and lower Outlier limits were set as PR/WCPR of 0.5 and 1.1 respectively.

It should be noted that a too tightly defined fixed outlier filter can significantly influence the calculated degradation rates. For example, Figure 2 presents the frequency distributions of the 5minute PR's calculated for system "8 Kaneka" across the entire data set (left), 2009 (middle) and 2015 (right). The light blue shaded regions denote the data that falls within the 25th and 75th quartiles, calculated from the entire data set. The solid horizontal lines denote the median value in each period. For this system, if the outlier filter limits were defined by the 25th and 75th quartiles calculated from the entire dataset, Figure 2 illustrates how in 2009 the analysis would exclude a significant proportion of the PR data at the high end of the spectrum. This would result in an underestimation of the PR for that year and would ultimately lead to an underestimation of the calculated degradation rate.

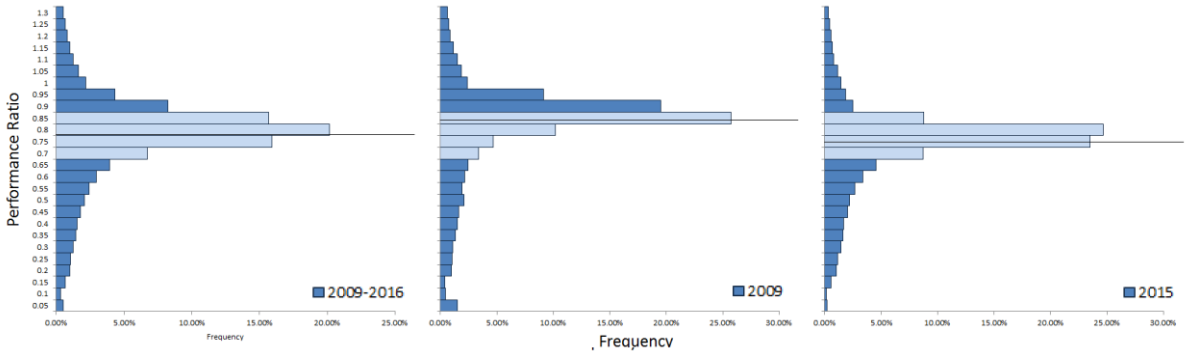

Figure 2: System 8 Kaneka – Frequency distributions of 5 minute degradation rates. Light blue regions denotes the data that falls within the upper and lower 25% quartile range calculated on the full dataset between 2009 and 2016.

4. Rolling Window Quantile Filter – Rather than applying a tightly defined fixed outlier filter, this paper utilised a 12 month moving average of the upper and lower 20% quantiles. The limits are calculated from the calculated distributions of the PR/WCPR data after filters 1 to 3 have been applied.

The combined effects of applying the filters in a stepwise process are presented in Figure 3 to Figure 8, as applied to system '3 BP Solar'.

3. PV Systems and Weather Data

3.1. DKASC

The PV system data for the location of Alice Springs was sourced from the Desert Knowledge Australia Solar Center (DKASC). The aim of the DKASC is to promote understanding and confidence in solar technologies by providing the industry with long term system level data. The DKASC currently measures, records and publishes PV performance data from 37 PV systems covering a variety of technologies, manufacturers and configurations. In addition, the DKASC also measures a number of weather variables of interest including, global and diffuse horizontal irradiance (ghi and dhi), ambient air temperature (T_a) and wind speed (WS). It is important to note that irradiance measurements recorded at the DKASC are measured using a Delta T SPN 1 Sunshine Pyranometer, which has a stated accuracy whereby 95% of readings will be within an interval of ±8%±10 W/m^2.

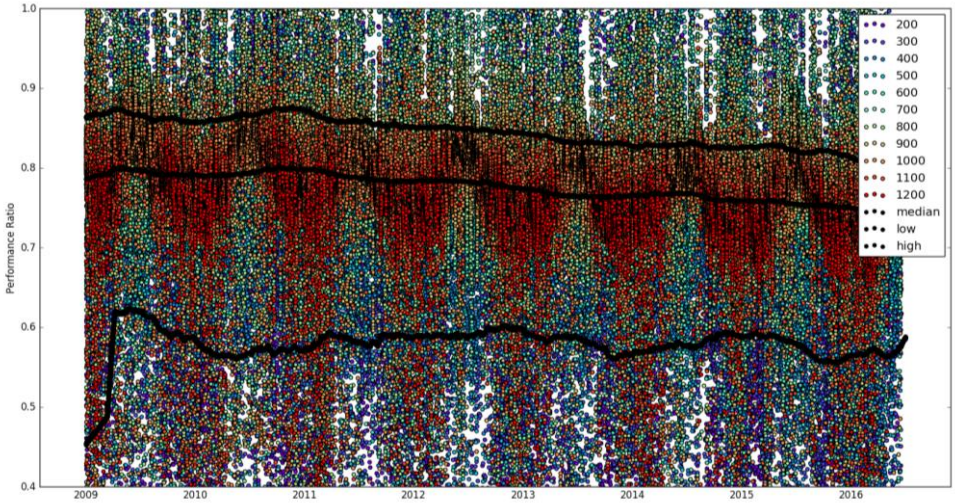

Figure 3: Performance Ratio (PR) – No filters applied

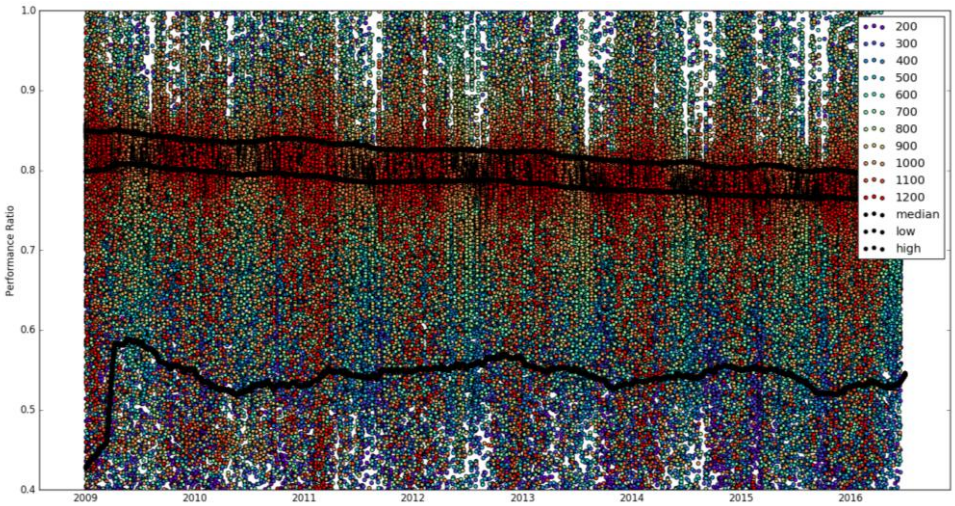

Figure 4: Weather Corrected Performance Ratio (WCPR) – No filters applied

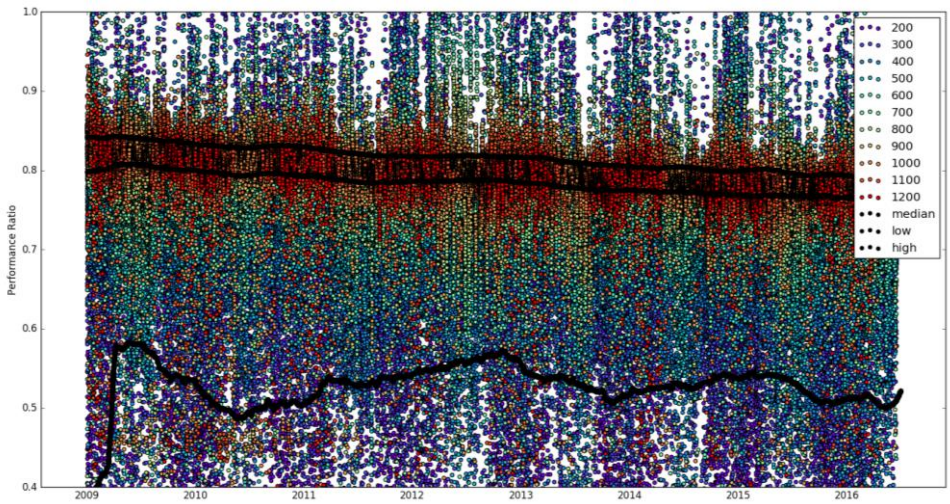

Figure 5: WCPR – Stability filters applied

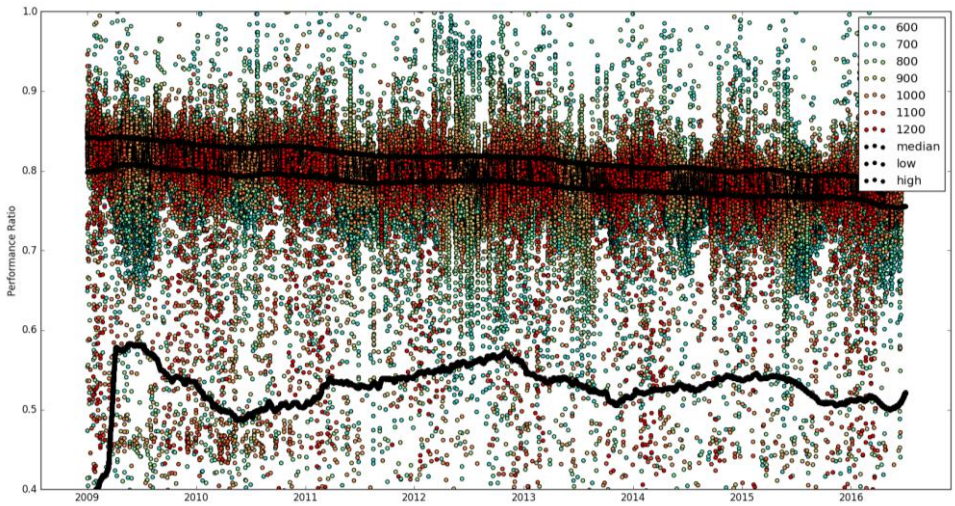

Figure 6: WCPR – Stability filters applied only POA > 600 W/m^2 displayed

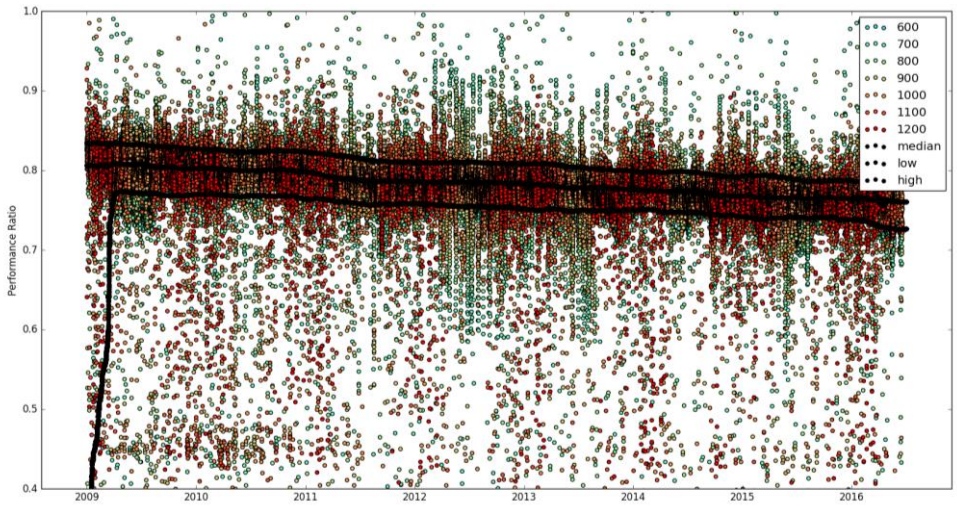

Figure 7: WCPR – Stability and POA irradiance filters applied

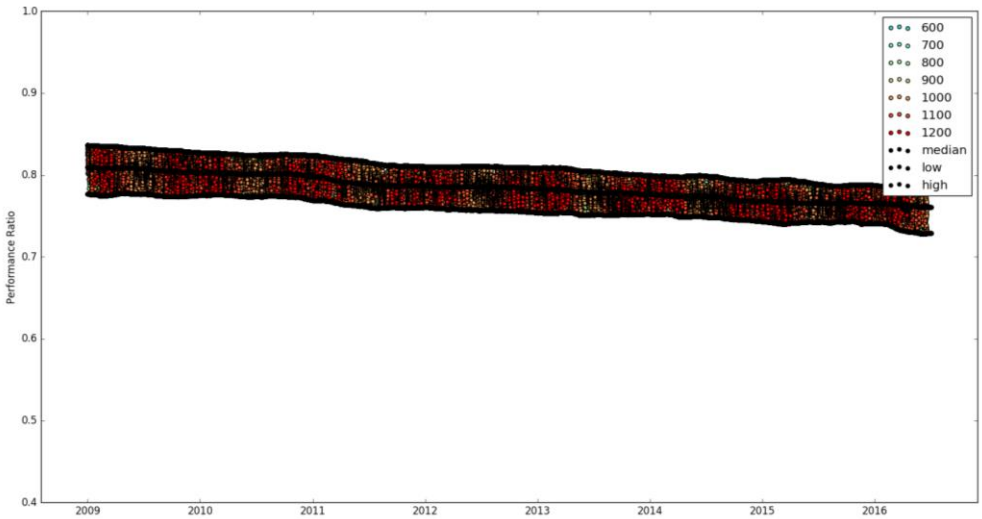

Figure 8: WCPR – All filters applied

The data utilised in this study was accessed via the DKASC online portal (DKASC 2016). The DKASC systems included within this study, and their specifications, are presented in Table 2. A number of the systems at the DKASC were excluded from this analysis for a variety of reasons. For example, systems installed after 2012 were excluded to ensure a minimum of approximately 3 years of available data. Similarly, all the tracking systems located at the DKASC were excluded, as over time these systems have suffered from failures due to the tracking mechanisms, resulting in changes to the system configurations over time i.e. a number of the systems are now located in a fixed position.

Table 2: DKASC System specifications (All systems Tilt = 20°, Orientation = North)

PV System	Array Rating (kWp)	Technology	Year	Tcoeff (%/°C)	Panel Type
3 BP Solar	4.95	poly-Si	2008	-0.41	BP 3165
8 Kaneka	6	Amorphous	2008	-0.25	Kaneka G-EA060
10 SunPower	5.805	mono-Si	2009	-0.38	SunPower SPR-215-WHT-I
11 BP Solar	4.95	poly-Si	2008	-0.41	BP 3165N
12 BP Solar	5.1	mono-Si	2008	-0.40	BP 4170N
13 Trina	5.25	mono-Si	2009	-0.45	Trina TSM-175DC01
14 Kyocera	5.4	poly-Si	2008	-0.46	Kyocera KD135GX-LP
16A BP Solar	1.98	poly-Si	2008	-0.41	BP 3165J
17 Sanyo	6.3	HIT	2010	-0.30	Sanyo HIP-210NKHE5
18 SunPower	5.236	mono-Si	2011	-0.38	SunPower SPR-238-WHT-D
19 Sungrid	5.04	mono-Si	2010	-0.46	Sungrid SG-280M6
20 Sungrid	5.04	poly-Si	2010	-0.41	Sungrid SG-280P6
21 Evergreen Solar	4.92	poly-Si	2010	-0.48	Evergreen ES-A-205-fa3
23 Calyxo	5.4	CdTe	2010	-0.25	CX-50
27 Hanergy	5.61	CIGS	2010	-0.45	SL1-85
33 REC	5.5	poly-Si	2012	-0.4*	No module reported.
34 Winaico	5.28	poly-Si	2012	-0.43	WSP-240P6

Of the available data for download, the primary field of interest in this study is the parameter of "5-Min-Avg kW". This parameter represents the average value of AC power in kW over each 5 minute period, averaged from one second readings. The measurements are captured with a Class 0.5 meter with ±0.5% accuracy (Ion 6200, CT: 50/5).

It should be noted that the DKASC data as of October 2016 had a number of observable time shift issues, in addition to the data collection issues already listed on the "Notes on the Data" page of the DKASC website. These issues were:

- Incorrect and inconsistent use of timestamps. Three 30 minute shifts were observed in the datasets. These time shifts were noted by visually comparing the ghi time series data from the DKASC to 5 minute averages of the one-minute measurements of ghi from the BoM for the nearby measurement location at Alice Springs airport. These time shifts were observed to occur on the following dates: 01/01/2010; 05/03/2010; 25/08/2015. These observed time shifts were corrected for in this analysis.

- System "23 Calyxo" appeared to have a 30 minute time shift in the PV data in comparison to the weather sensor and PV output data from the other systems pre 2014. This observed time shift was corrected for in this analysis.

3.2. Australian Bureau of Meteorology (BoM)

In addition to the onsite measurements of the weather variables, half-hourly observations of temperature and wind speed were sourced from the Australian BoM from the automatic weather station (AWS) located at the Alice Springs airport. The half hourly records were resampled by the method of linear interpolation, to coincide with the 5 minute recorded frequency of DKASC data. The AWSs operated as part of the BoM network are maintained to the accuracies reproduced in Table 3 by maintenance visits at least twice a year (Bureau of Meteorology 2005).

Table 3: Accuracies of AWS operated by the Australian Bureau of Meteorology (Bureau of Meteorology 2005)

Sensor	Range	Accuracy	Unit
Air temperature	-25 to +60	0.3	°C
Wind Speed	2 to 180	2	knot

Surface and satellite derived observations of irradiance for the location of Alice Springs, were also sourced from the BoM. The surface observations were accessed via the BoM One Minute Solar Data portal (Bureau of Meteorology 2015). This study utilised the available data as of June 2016 for the measurement station located at the Alice Springs airport. The one minute solar data was resampled to 5 minute averages of the 1 minute data, to coincide with the recorded interval of the DKASC data. The product notes for the one-minute solar radiation data (Bureau of Meteorology 2014) indicates that the uncertainty associated with each solar statistic reported has been calculated using ISO guidelines and are traceable to the World Radiometric Reference for solar components. Similarly, it is reported that the data quality control and assurance is such that the 95% uncertainty for any quantity measured is well within the original network targets of 3% or 15 W/m^2 (whichever is greater) after the post measurement verification is complete (Bureau of Meteorology 2014).

The gridded satellite derived data is processed by the Australian BoM from satellite imagery sourced from the Geostationary Meteorological Satellite and MTSAT series operated by the Japan Meteorological Agency and from GOES-9 operated by the National Oceanographic & Atmospheric Administration (NOAA) for the Japan Meteorological Agency. The accuracy of the hourly gridded satellite derived irradiance data products, in comparison to 25-minute averaged GHI measurements from the BoM surface-based measurements of irradiance, as reported by the BoM, are presented in Table 4. Similar levels of accuracy were reported in (Copper et al. 2015), for the previous version of the BoM satellite derived dataset (2015) when analysed in comparison to hourly averages of measured GHI.

Table 4: Statistical metrics of the bias and uncertainty of the BoM hourly gridded satellite derived irradiance data products

	(Bureau of Meteorology 2016) – All sites		Alice Springs (this study)	
	GHI (W/m^2)	DNI (W/m^2)	GHI (W/m^2)	DNI (W/m^2)
MBE (W/m^2)	-1	-3	-11	-19.4
RMSE (W/m^2)	76	172	69.6	155.8

4. Results

Table 5 presents the calculated degradation rates, for the various combinations of the statistical methods, performance metrics and input weather data, for the DKASC systems located in Alice Springs. The results highlight that a significant amount a variation occurs across the calculated degradation rates, dependent on the methodology chosen. 'N/A' results are reported for those systems and method combinations that have less than 3 years of data available for the analysis. This occurs for the PV systems installed in 2012 in combination with the CSD methodology. This is a result of the fact that the CSD methodology inherently losses 12 months of data as it is based on a 12 month moving average. It should be noted that the exact same data cleaning process was undertaken for all scenarios.

Table 5: Calculated degradation rates (%/year) for DKASC (Alice Springs)

PV System	BoM Weather Parameters				DKASC Weather Parameters				Satellite
	WCPR		PR		WCPR		PR		WCPR
	LR	CSD	LR	CSD	LR	CSD	LR	CSD	LR
3 BP Solar	-0.68%	-0.68%	-0.69%	-0.75%	-0.90%	-0.91%	-0.99%	-1.05%	-0.41%
8 Kaneka	-1.53%	-1.28%	-1.55%	-1.36%	-1.73%	-1.54%	-1.75%	-1.61%	-1.47%
10 SunPower	-0.59%	-0.60%	-0.61%	-0.69%	-0.79%	-0.82%	-0.89%	-0.97%	-0.24%
11 BP Solar	-0.44%	-0.41%	-0.45%	-0.50%	-0.64%	-0.63%	-0.74%	-0.79%	-0.16%
12 BP Solar	-0.29%	-0.18%	-0.35%	-0.27%	-0.51%	-0.42%	-0.66%	-0.58%	-0.03%
13 Trina	-0.93%	-0.91%	-1.07%	-1.13%	-1.16%	-1.18%	-1.38%	-1.48%	-0.72%
14 Kyocera	-0.64%	-0.60%	-0.67%	-0.72%	-0.85%	-0.83%	-0.97%	-1.03%	-0.29%
16A BP Solar	-0.86%	-0.77%	-0.84%	-0.85%	-0.94%	-0.87%	-1.07%	-1.08%	-0.43%
17 Sanyo	-1.44%	-1.35%	-1.62%	-1.50%	-1.73%	-1.68%	-2.00%	-1.89%	-1.20%
19 Sungrid	-0.84%	-0.76%	-1.08%	-0.95%	-1.10%	-1.05%	-1.46%	-1.32%	-0.50%
20 Sungrid	-0.93%	-0.80%	-1.13%	-0.96%	-1.25%	-1.16%	-1.57%	-1.39%	-0.55%
21 Evergreen Solar	-0.70%	-0.55%	-0.96%	-0.75%	-0.97%	-0.85%	-1.35%	-1.13%	-0.33%
23 Calyxo	-1.25%	-1.05%	-1.41%	-1.22%	-1.51%	-1.37%	-1.71%	-1.54%	-1.05%
27 Hanergy	-0.61%	-0.53%	-0.78%	-0.76%	-0.81%	-0.80%	-1.08%	-1.08%	0.07%
33 REC	-0.81%	N/A	-0.53%	N/A	-1.20%	N/A	-1.22%	N/A	-1.07%
34 Winaico	-0.41%	N/A	-0.07%	N/A	-0.93%	N/A	-0.84%	N/A	-0.25%
Mean	-0.81%	-0.75%	-0.86%	-0.89%	-1.07%	-1.01%	-1.23%	-1.21%	-0.54%
Median	-0.75%	-0.72%	-0.81%	-0.80%	-0.95%	-0.89%	-1.15%	-1.11%	-0.42%

Generally, it was noted that higher degradation rates were calculated when the analysis was undertaken using the weather data measured onsite at the DKASC. This increase was found to be caused by an observed difference between the values of irradiance measured at the DKASC and the BoM measurement station located at the Alice Springs airport (~5km apart). In particular, it was noted that the difference between the measurements recorded at the two locations became more apparent from 2013 onwards. This appeared to coincide with the time period where the pyranometer at the DKASC underwent calibration in mid-December 2012. Generally, from 2013 onwards, DKASC measured higher levels of irradiance, resulting in lower levels of PR/WCPR and hence higher calculated degradation rates. Based on the quality/accuracy of the measurement setup at the two locations, the weather data collected by the BoM at Alice Springs airport will be the more accurate weather data set. Hence, the lower

degradation rates calculated using the BoM weather data are likely to be more reflective of the degradation rates of the DKASC systems in Alice Springs.

The calculated degradation rates using the BoM Satellite derived irradiance data, in conjunction with the WCPR-LR method, again indicates very different results to those calculated with the high quality ground measured irradiance data from the BoM. A visual inspection of the weekly WCPR trend lines, applied to system '3 BP Solar', are presented in Figure 9. The figure indicates that the trend line calculated using the BoM satellite data has a number of pertinent issues that will affect the calculated degradation rate. An analysis of the two trend lines indicated a negative correlation (ρ = -0.75) between the observed differences and the level of bias calculated within the BoM satellite derived dataset for Alice Springs over this time period. Due to the inconsistent bias within the BoM satellite derived irradiance, this dataset in its current form is not appropriate for use in degradation calculations. These two sets of results highlight the importance of good quality irradiance data for degradation rate studies.

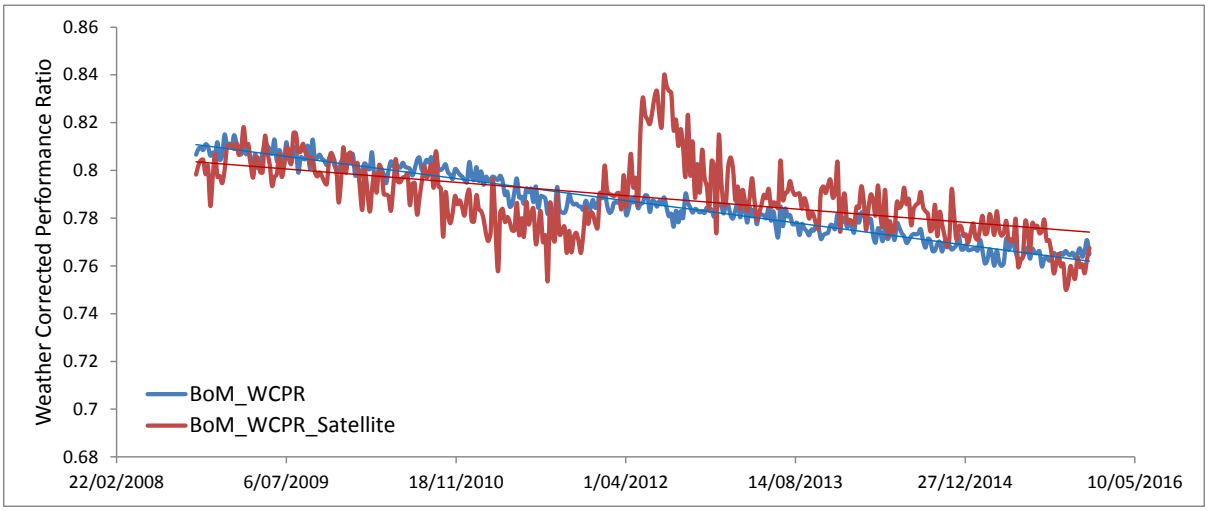

Figure 9: Weekly WCPR of system 3 BP Solar – Influence of BoM Irradiance data

One interesting subset of the data are the poly-Si BP Solar systems, systems 3, 11 and 16A. These three systems are all constructed using the same module technology. What makes the subset interesting is that systems 11 and 16A are essentially identical, providing a test of redundancy in the calculated degradation rate of the BP Solar poly-Si technology under rack mounted conditions. Further, system 3 is a roof mounted array whilst systems 11 and 16A are rack mounted arrays. This subset provides us with the ability to test whether the mounting configuration has an impact on the degradation rate of the system i.e. the roof mounted array in theory will reach higher cell temperatures and therefore could degrade at a faster rate.

The results presented in Table 5 indicate that the degradation rates of systems 11 and 16A are not identical. In fact, the degradation rate of system 16A is almost double the rate of system 11. Figure 10 plots the weekly WCPR of the three BP Solar poly-Si systems at DKASC. This figure indicates that system 11 and system 16A were degrading at a similar rate up until 2015, after which time system 16A began to degrade at a much faster rate. The cause of the increase in the degradation rate of system 16A was not investigated in this study. However, the degradation rates of these three systems were recalculated using the six years of data prior to 2015. Table 6 presents these results and illustrates that prior to 2015, systems 11 and 16A were degrading at an almost identical rate of 0.48%/year. In comparison, system 3, the roof

mounted array, was degrading at a faster rate than the rack mounted systems of the same module technology at 0.68%/year.

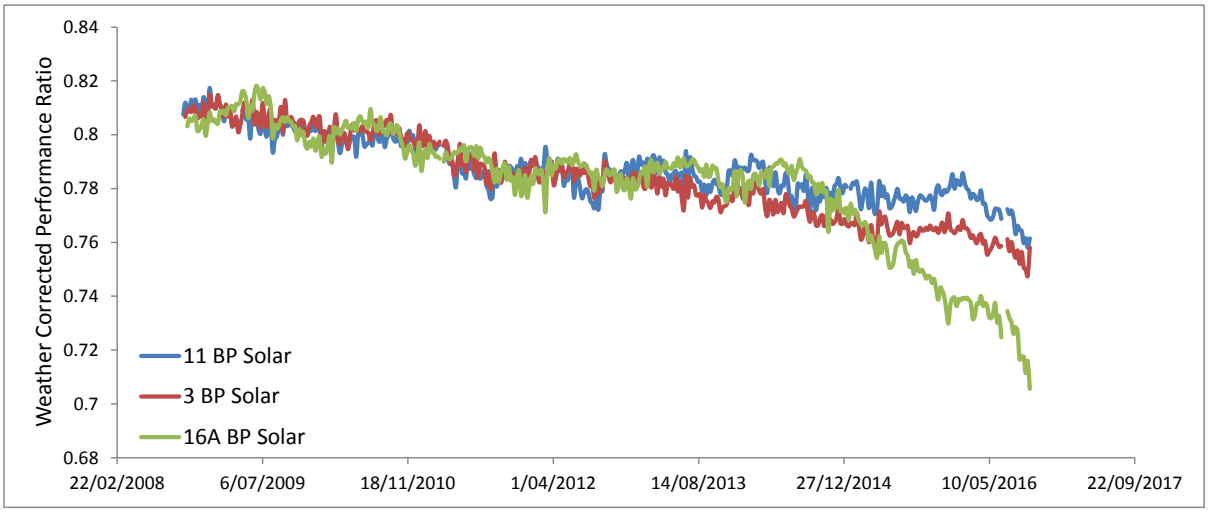

Figure 10: Weekly WCPR of the DKASC poly-Si BP Solar Systems

Table 6: Results for the DKASC poly-Si BP Solar Systems pre 2015

PV System	BoM Weather Parameters				DKASC Weather Parameters			
	WCPR		PR		WCPR		PR	
	LR	CSD	LR	CSD	LR	CSD	LR	CSD
3 BP Solar	-0.68%	-0.69%	-0.66%	-0.76%	-0.82%	-0.82%	-0.83%	-0.91%
11 BP Solar	-0.48%	-0.44%	-0.46%	-0.52%	-0.61%	-0.57%	-0.63%	-0.68%
16A BP Solar	-0.48%	-0.49%	-0.38%	-0.53%	-0.59%	-0.59%	-0.59%	-0.70%

The other interesting subsets of the data are the non-crystalline silicon based arrays i.e. systems 8, 17 and 23. These systems are of amorphous, HIT and CdTe technology, and as would be expected for these technologies, they undergo a period of initial degradation, see Figure 11, before stabilising to their expected level of performance and degrading at a much more stable rate. These two regions, with their fitted linear trend line are highlighted within Figure 11 for system '23 Calyxo'. This causes these systems to have on first appearance degradations rates that are significantly higher than the poly-Si and mono-Si technologies, as indicated in Table 5. However, calculations of the degradation rates of these systems, after the initial period of degradation, indicates that the degradation rates of these technologies fall within the range of degradation rates observed for the crystalline silicon technologies at DKASC, Table 7.

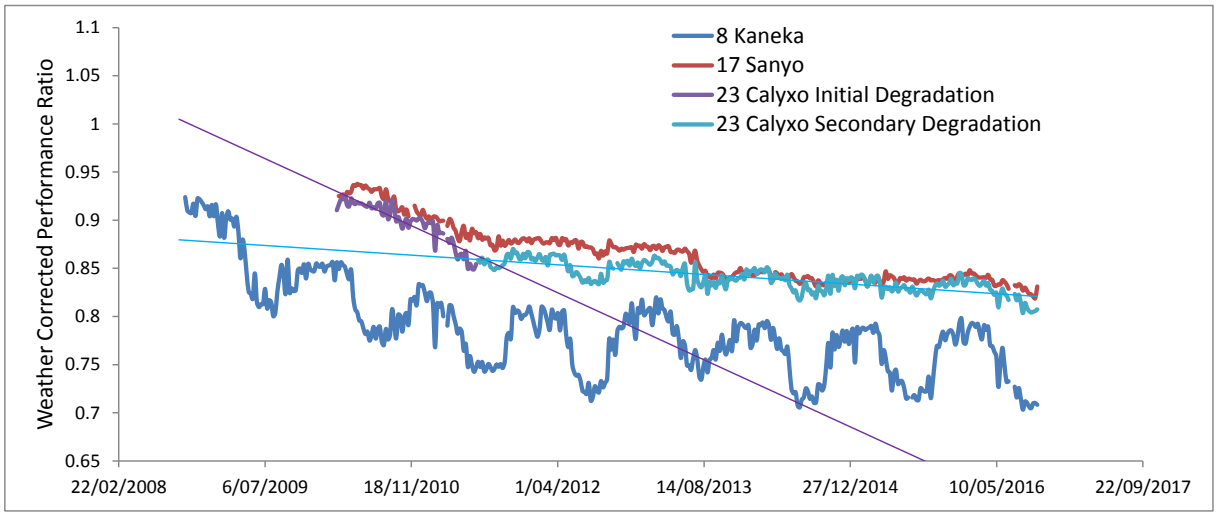

Figure 11: Weekly WCPR of DKASC Systems 8, 17 and 23

Table 7: Calculated degradation rates (%/year) for DKASC Systems 8, 17 and 23 during excluding the initial period of high degradation

PV System	BoM Weather Parameters				DKASC Weather Parameters			
	WCPR		PR		WCPR		PR	
	LR	CSD	LR	CSD	LR	CSD	LR	CSD
8 Kaneka	-0.68%	-0.61%	-0.75%	-0.72%	-1.01%	-0.99%	-1.08%	-1.11%
17 Sanyo	-1.15%	-1.23%	-1.23%	-1.35%	-1.45%	-1.57%	-1.63%	-1.75%
23 Calyxo	-0.72%	-0.66%	-0.78%	-0.76%	-1.12%	-1.14%	-1.19%	-1.26%

5. Conclusion

This study calculated the AC power degradation rates (%/year) of a subset of the PV systems located at the Desert Knowledge Australia Solar Centre (DKASC). Degradation rates were calculated using a variety of methods and input irradiance data sources. The results demonstrated that a high level of variation can occur across the calculated degradation rate based on the selected methodology and input weather data. Importantly, this study determined that degradation rates cannot be calculated via the use of the BoM satellite derived irradiance dataset due to inconsistent bias in the dataset over time. The importance of good quality irradiance data for degradation studies was highlighted.

For the combined WCPR-LR method, the mean and median reported annual degradation rates were 0.81% and 0.75% respectively. These values decrease to 0.68% and 0.69% respectively for x-Si technologies and to 0.7% and 0.69% per annum when the mean and median degradation rates for the non x-Si technologies are calculated once the performance has stabilised after initial exposure. Finally, the results from this study (albeit with a sample size of 1) indicate that the mounting configuration of PV systems has an impact on the degradation rate of the system, with the roof mounted system degrading at a significantly faster rate than the same module technology in a rack mounted configuration.

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