LOW CARBON LIVING CRC

Intelligent automated monitoring of commercial photovoltaic (PV) systems

Final report

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To learn more about CRC Low Carbon Living visit: www.lowcarbonlivingcrc.com.au.

To learn more about Solar Analytics visit: www.solaranalytics.com.au.

Disclaimer

Peer Review Statement

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Acronyms

BOM	Bureau of Meteorology
CRC	Cooperative Research Centre
DKASC	Desert Knowledge Australia Solar Centre
GHI	Global Horizontal Irradiance
MBD	Mean Bias Deviation
PID	Potential Induced Degradation
POA	Plane of Array
PV	Photovoltaic
RMSD	Root Mean Squared Deviation
NLA	Net Lettable Area
NABERS	National Australian Built Environment Rating System

Executive Summary

Rapid growth of distributed small scale Photovolatic (PV) systems has increased the need for tools that can undertake reliable real time monitoring of system performance with the capability to detect and diagnose underperformance at the earliest possible stage. This project refined the system performance algorithms within Solar Analytics, a PV systems monitoring tool offered by Suntech, to improve their accuracy and to test their ability to predict the performance of residential and commercial PV systems. This project also developed an initial set of algorithms to detect and diagnose underperformance. The project also investigated the feasibility of (1) including forecasts of PV system performance within Solar Analytics and (2) the integration of commercial building energy management systems with Solar Analytics to provide a holistic energy management platform for the small to medium sized commercial office buildings market.

PV System Performance Algorithms

Solar Analytics is a program developed from a set of algorithms used to predict the AC electrical output of PV systems. Suntech provided their initial version of Solar Analytics as the starting point of this CRC project. The accuracy of the overall performance of this initial version of Solar Analytics and the individual algorithms that constitute it were tested in comparison to 5 months of measured data from 17 PV systems located across Sydney with supplementary data from systems located at the Desert Knowledge Australia Solar Centre (DKASC) in Alice Springs, NT and a system located in Nyngan, NSW. The initial test of Solar Analytics on the 17 PV systems across Sydney achieved a daily prediction of AC power with average levels of normalised bias and uncertainty of -7% and 22% respectively, with individual system biases between -18% and 65% and uncertainties between 12% to 73%.

The analysis of the individual algorithms that constituted the initial version of Solar Analytics revealed that the program was unable to handle amorphous PV systems or PV systems with multiple panel orientations or tilt angles. These issues were resolved in the algorithm refinement process undertaken as part of this CRC project. The assessment of the initial version of Solar Analytics also revealed that the primary driver of uncertainty in the estimate of AC power was the input of irradiance data. Generally, PV performance models use inputs of plane of array (POA) irradiance and module temperatures in conjunction with details on the system configuration to estimate the DC and AC output of a PV system. Ideally, onsite measurements of POA irradiance and module temperature would be available as input into the PV performance algorithms. Unfortunately these parameters are rarely measured for small scale and commercial PV systems due to the costs associated with the purchase, setup and maintenance of the required measurement system. Hence the ability to accurately estimate the AC output of PV systems becomes dependent on the accuracy of the method used to estimate POA irradiance.

The clear sky adjusted algorithm used within the initial version of Solar Analytics to estimate global horizontal irradiance (GHI) and then POA irradiance is essentially the methodology that should be employed under the worst case scenario when no onsite or nearby measurements of POA irradiance, GHI or AC power from another PV system are available. As part of this CRC project a series of algorithms were developed to improve the estimate of GHI based on measurements of AC power, POA irradiance or GHI from nearby locations. This project also defined criteria to determine appropriate nearby PV systems/locations.

Testing of the refined algorithms proposed for Solar Analytics, based on 1 complete year of data for three PV systems located across Sydney, revealed that when onsite measurements of POA irradiance were available, Solar Analytics could estimate the AC performance of the PV systems with levels of bias and uncertainty below 3% and 6% respectively at the daily level. In the absence of measured POA irradiance the results indicated that modelling uncertainty increased significantly when alternative methods to estimate POA irradiance were used. The analysis also highlighted that POA irradiance estimated via the use of measured POA or AC power from a nearby PV system offered modelling advantages over the post processed hourly gridded satellite derived irradiance dataset from the Australian Bureau of Meteorology (BOM), if the location of the nearby PV system was in close proximity to the PV system under study.

A number of potential schemes were also developed that could be implemented within Solar Analytics to monitor the performance of PV systems with the aim to identify when a system is underperforming or at fault and the cause of the underperformance/fault. The proposed schemes would enable Solar Analytics the ability to diagnose zero AC power faults, shading due to fixed elements like buildings or trees, string faults and potential induced degradation (PID) faults. Unfortunately due to the lack of measured PV system data with faults, the schemes and algorithms provided are only the initial phase of developing a robust diagnostic capability. Testing of these initial algorithms and further refinement of the algorithms are recommended.

Building Energy Monitoring Management

The second major outcome from this project was a feasibility investigation into the current commercial building energy management systems, and the potential to integrate the PV system prediction algorithms to provide a simple and holistic energy management platform for the small-medium sized commercial office buildings market. It was found that understanding the energy performance of the building compared with itself or other buildings is important due to large

support for NABERS Energy nationwide. It was also found that corrective actions automatically generated from a system similar to Solar Analytics is likely to be generic and of little value in the market as it is freely available.

PV System Performance Forecasting

The third output from this project was a report that summarises the potential applicability of combining weather forecasting with the PV performance algorithms within Solar Analytics to predict the future energy generation of PV systems. Three primary methodologies were identified for forecasting GHI depending on the time scale of the required forecast. The three irradiance forecasting methods based on the time scale of the horizon forecast are:

- Very short term forecasts ranging from minutes to a few hours
- Short term forecasts ranging from a few hours up to 6 hours ahead
- Longer term forecasts.

The review indicated that the very short to short term irradiance forecasting methods maybe applicable for integration with Solar Analytics, suggesting a worthy area of further research.

Introduction

To optimise the performance of photovoltaic systems, especially within the commercial space, it is essential to have an effective tool to both measure and simulate the performance of PV systems. This requires three key elements:

- Actual system energy yield (AC and DC power, voltage and current)
- Local weather data (irradiance, ambient temperature and wind speed)
- Sophisticated algorithms to predict energy generation

The prediction algorithms estimate how much energy the system should have produced under the actual site conditions, and intelligently compare this to the actual energy yield to accurately determine if the system is performing within expectations.

Although there are several PV monitoring tools on the market, none of these solutions provide a means of comparison to expected yield under the same weather conditions. The proposed monitoring tool will fill the gap in the market where expected energy generation is fairly compared to actual energy generation.

Suntech Power Australia's Applied PV department has in partnership with Envais Solar developed Solar Analytics as a tool for the measurement and simulation of PV system performance for residential users. This project used this background intellectual property (IP) to advance its application in small commercial buildings and to engage with CRC partners in its development and implementation.

The refined monitoring tool is able to record and analyse the building energy consumption data, thus providing a single intelligent platform to understand, monitor and optimise the buildings total energy usage consumption and patterns.

The key research areas that were conducted were:

- Refined algorithms for simulating photovoltaic energy generation algorithms for commercial installations
- Refined algorithms for diagnosing the cause of any underperformance
- Feasibility study into the demand for and viability of a similar modelling approach for the monitoring of energy consumption in commercial buildings
- Investigation into the potential future development of energy generation forecasting

The monitoring tool that was improved under this project will have application in small to medium commercial systems, and will provide a monitoring solution that will document performance against prediction and monitoring will improve confidence in PV system integration and lead to better PV yields and better building energy management.

Background

Solar Analytics is a unique solar monitoring product that uses sophisticated algorithms to analyse the energy generated by a PV system, and compare this to the calculated energy yield based on the PV system parameters and daily weather conditions. These algorithms intelligently assess how well a PV system is performing, and inform the solar system installer and owner so that underperforming systems can be rectified in a timely manner.

Solar Analytics (SA) is a project undertaken through a partnership between Suntech Power, one of the world's largest PV module manufacturers, and Envais Solar, an Australian solar technology company.

Suntech R&D Australia Pty Ltd (SRDA) is a wholly owned subsidiary of Suntech Power, one of the world's leading photovoltaic manufacturers. Founded by eminent solar scientist and Australian citizen Dr. Zhengrong Shi in 2001, Suntech utilises crystalline silicon PV technology based on thirty years of collaborative research with the University of New South Wales (UNSW), and spends over $5 million in Australia each year on research and development activities managed by SRDA.

SRDA works closely with Suntech Power Australia Pty Ltd, both companies being subsidiaries of Suntech Power. Suntech Power Australia is the commercial sales arm of Suntech throughout Australia, and has sold over 1.5 million photovoltaic modules in Australia.

Opportunity

Globally there are more than 5 million PV systems installed, and over 1.2 million PV systems installed across Australia, however less than 1% of these Australian systems have any effective form of monitoring or ability to determine how well the system is performing. More than 98% of the current Australian market consists of residential systems under 10kW, with an increasing number of commercial systems between 10kW and 100kW being installed.

In the absence of a cost effective, robust and useful monitoring system, these customers are unable to answer the fundamental question "How well is my PV system performing". This lack of information is costing them hundreds to thousands of dollars per year in lost revenue.

> *" Analysis of Ausgrid data from over 8000 PV systems in NSW shows that approximately 50% of these PV systems are underperforming. This is broadly consistent with analysis of Australia wide system performance data" - SunWiz, 2013*

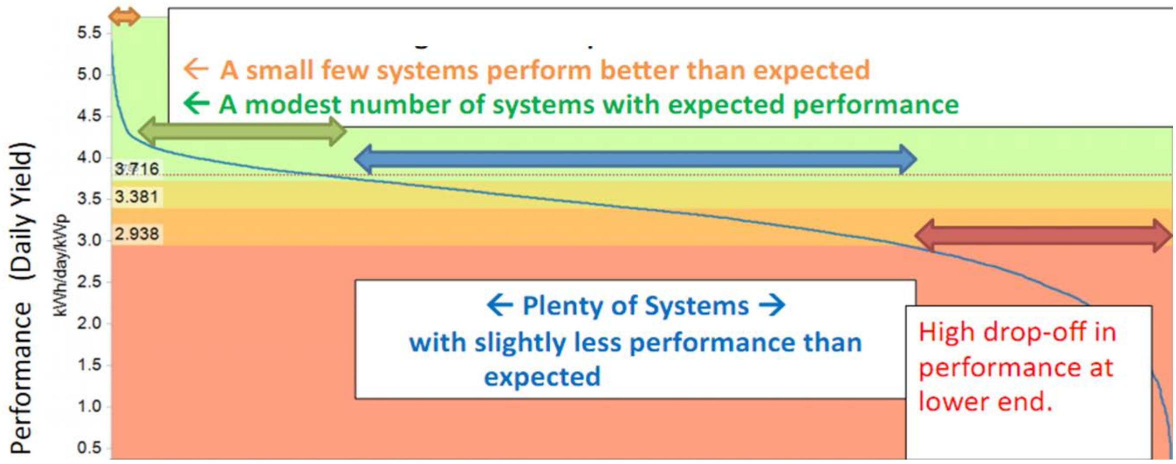
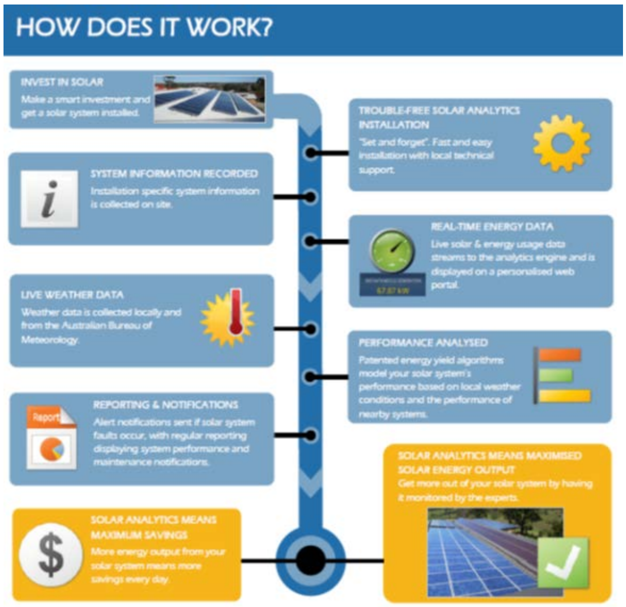


Figure 1 SunWiz data showing system underperformance [1]

PV System Performance Algorithms

Modelling



Rapid growth of distributed small scale photovoltaic (PV) systems (typically under 100kW) has increased the need for tools that can undertake reliable real time monitoring of system performance with the capability to detect and diagnose underperformance at the earliest stage possible. To assess underperformance, real time (or close to real time) measurements of PV systems are typically compared to the theoretical performance of the systems during the same time period. The reliability of such monitoring/diagnostics tools is dependent on the accuracy of the algorithms used to model the theoretical performance and the accuracy of the inputs used within the models.

Generally, PV performance models use inputs of plane of array (POA) irradiance and module temperatures in conjunction with details on the system configuration to estimate the DC and AC output of the PV system. Ideally, onsite measurements of POA irradiance and module temperature would be available as input into the PV performance models. Unfortunately these parameters are rarely measured for small scale PV systems due to the costs associated with the purchase, setup and maintenance of the required measurement system. Hence the ability to accurately model the AC output of a PV system becomes dependent on the accuracy of the method used to estimate real time POA irradiance and module temperature.

To overcome the lack of onsite measured data, a number of mathematical models have been developed to estimate POA irradiance [2-9] and module temperature [10-16] which are typically dependent on inputs of horizontal global, diffuse and direct irradiance. The accuracy of these models has been investigated in detail at the individual model level. However there has been limited focus on how the use and combination of these models influence the accuracy of the PV performance models. In addition, the use of satellite derived global horizontal irradiance has been used for fault detection and monitoring of PV systems in Europe and Africa [17-19]. Unfortunately in Australia, hourly satellite derived irradiance is not currently available in real time, ruling out the use of Satellite derived irradiance as input for real time monitoring of PV systems in Australia.

Literature Review

In the absence of measured POA irradiance a number of irradiance transposition models have been developed to estimate POA irradiance from inputs of horizontal global, diffuse and direct irradiance. A comprehensive study of the accuracy of the transposition models found within the literature has been undertaken [5]. The accuracy of these models have been tested extensively for northern hemisphere locations [3-9] and one southern hemisphere location [2]. Confidence in the accuracy of these transposition models is confirmed via industry wide utilisation of these models within standard PV modelling packages like PVSyst [20] and NREL's System Advisor Model (SAM) [21]

In the absence of measured diffuse and direct irradiance, measurements of global horizontal irradiance can be separated into the diffuse and direct components via an irradiance separation model. Again a number of mathematical models are found within the literature demonstrating the accuracy of these separation models [22-26]. Similarly, global horizontal irradiance can also be derived from other remote measurements like satellite imagery, measurements of global horizontal or POA irradiance from another location or measurements of AC output from PV systems from another location [27]. In the worst case scenario global horizontal irradiance can be estimated via a clear sky model [28]. The use of satellite derived global horizontal and direct normal irradiance has become common place in Europe, Africa and North America for PV performance modelling when measured values of irradiance do not exist. Work presented in [17-19] investigated the effects of using satellite derived irradiance in designing and monitoring PV systems in Europe and Africa. The results from [18] indicated that the satellite data over estimated solar irradiance and hence underestimated the required PV system size for an off-grid application in South Africa, whilst the results in [17, 19] indicated that the uncertainty (RMSE of 11%) of the satellite derived irradiance data prevented the detection of small energy losses within the monitored PV systems. Unfortunately real time hourly satellite derived irradiance is not currently available within Australia ruling out satellite derived irradiance as a potential input for modelling PV performance in real time.

In the absence of measured module temperatures a number of models have been developed to estimate module temperatures based on inputs of POA irradiance, ambient temperature and other parameters such as wind speed and mounting configuration. As was the case for POA irradiance models, the module temperature models have been extensively tested for northern hemisphere locations [10-16]. Although these models have been shown to achieve good results at the model level when the correct model coefficients are chosen, little detail or direction is usually provided with reference to which set of model coefficients should be used under which scenario, particularly for the lay person who uses these models when incorporated within standard PV modelling packages like PVSyst and SAM. It was noted in [15, 16] that care should be exercised when applying a particular expression for the operating temperature of a PV module because the available equations had been developed with specific mounting geometries and module types.

System Architecture

The Solar Analytics infrastructure has been established to enable the future automation and cost effective application of the algorithms. This structure uses web 2.0 technology and cloud based data analysis (refer to Figure 2).

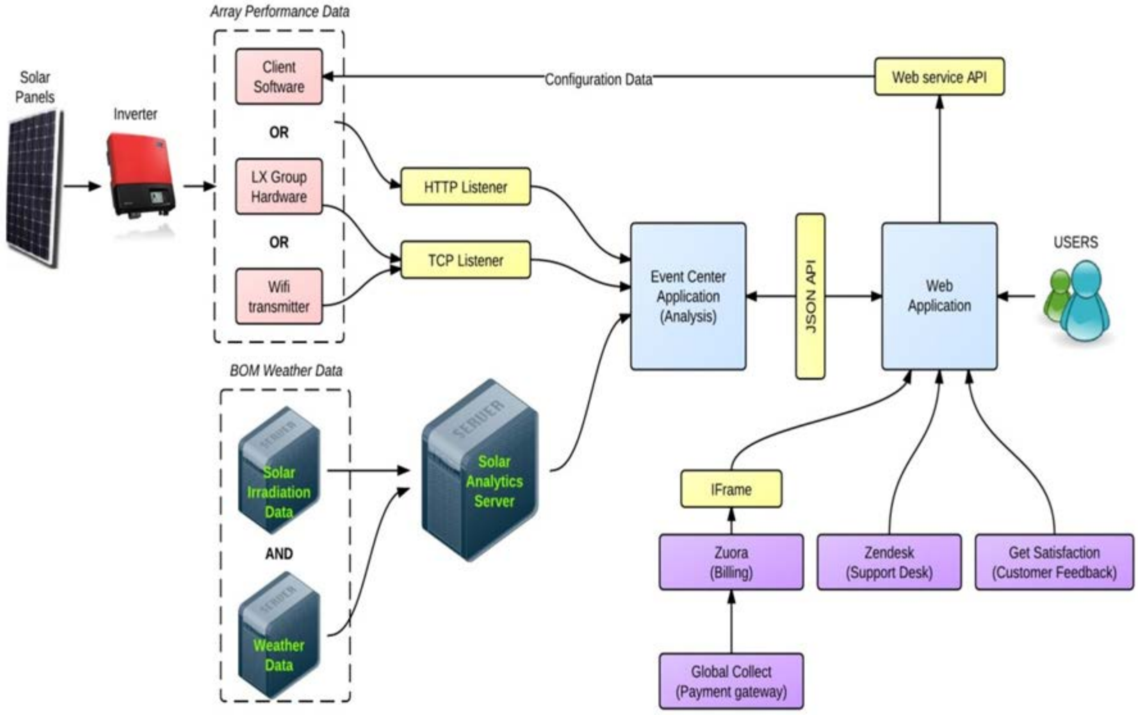


Figure 2 Architecture of monitoring infrastructure

The key functions are:

- Collect actual system energy generation data
- Collect local weather (irradiance, ambient temperature and wind speed) data
- Generate estimated energy using daily weather data
- Automated diagnosis of cause for any underperformance
- Inform customer of system performance and required actions if under-performing

Modelling Results – Analysis of the Initial version of Solar Analytics

This section presents the results of the performance analysis undertaken on the initial development platform (DP) version of Solar Analytics provided by Suntech at the start of this CRC project. The dataset used in the initial analysis was downloaded from the back end database of the initial version of Solar Analytics on the 17/10/12. At that point in time, data from 17 PV systems across Sydney were available. A number of these PV systems consisted of multiple arrays that were monitored by separate inverters. Each separate array was treated independently. Most of the 17 PV systems had 3 to 5 months' worth of data available between the periods of 19/04/12 to the 16/10/12. Processing of the raw data was undertaken to exclude missing or erroneous values. In addition two PV systems and 1 array of a third system were excluded from this initial analysis due to the inability of the original DP version of Solar Analytics to model PV systems that contained PV modules at varying tilts and orientations.

Figure 3 and Figure 4 present the daily and hourly scatterplots of predicted power from the initial DP version of Solar Analytics versus the measured array data of the PV systems. The figures indicate that the initial version of Solar Analytics achieved a reasonable correlation to the measured array data at the daily level with normalised levels of bias and uncertainty of -7.05% and 22.09% respectively. At the hourly level the figures demonstrate a significant increase in the level of uncertainty of the modelled results at 49.16%. This high level of uncertainty, particularly at the hourly level, would inhibit the ability of Solar Analytics to undertake underperformance diagnostics.

Each of the individual algorithms that constituted the initial version of Solar Analytics were tested independently for their accuracy to identify which algorithms were contributing to the high level of uncertainty in the modelled results. The analysis indicated that the method used to estimate global horizontal irradiance (GHI) contributed to approximately 50% and 80% of the modelled uncertainty when onsite measurements of hourly GHI and POA irradiance, respectively, were not available. Figure 5 presents an example of the normalised levels of bias and uncertainty at each of the major modelling stages, for a PV system located in Nyngan, NSW. The labels in the figure identify the dataset used as the starting point of the modelling within Solar Analytics. Further descriptions of these labels are presented below:

- Daily GHI – Modelling begins using the ASHRAE clear sky model adjusted to the daily level of insolation reported from the Australian Bureau of Meteorology (BOM) to estimate the hourly levels of GHI. All other parameters are modelled from this point forward.
- Hourly GHI – Modelling utilises measured values of hourly GHI as input into the modelling process to estimate direct normal irradiance (DNI) and direct horizontal irradiance (DHI). For the Nyngan example hourly values of GHI were derived from satellite imagery by 3Tier. All other parameters are modelled from this point forward.
- Hourly GHI, DNI and DHI – Modelling utilises measured values of hourly GHI, DNI and DHI as input. For the Nyngan example the values are not measured but were derived from satellite imagery by 3Tier. All other parameters are modelled from this point forward.
- Irradiance on Plane – Modelling utilises measured values of plane of array irradiance as input. All other parameters are modelled from this point forward
- DC Power – Modelling utilises measured values of DC power as input. All other parameters are modelled from this point forward.

Figure 5 indicates that a high level of modelled uncertainty occurs at the hourly level (41.5%) when only the daily GHI parameter reported from the BOM was available. When measured hourly values of GHI were available as input into the modelling process the level of uncertainty for the Nyngan example decreased to 20% (approx. 50% reduction in the level of modelling uncertainty). Similarly for the case where measured POA irradiance was available uncertainty further decreased to 8.32% (an 80% reduction in modelling uncertainty from the case where only daily GHI was available).

NB: In Figure 5 there is an observed increase in the level of uncertainty and bias when hourly GHI, DNI and DHI is used as input into the modelling process in comparison to the case where only hourly GHI is used as input. This result is not an anomaly, but is an artefact of this example which used satellite derived parameters of GHI, DNI and DHI as actual onsite measurements of these parameters were not available.

A second set of examples is presented in Figure 6 for four PV systems located within the Desert Knowledge Australia Solar Centre (DKASC) in Alice Springs. The systems include a roof mounted polycrystalline system and rack mounted monocrystalline, polycrysatalline and amorphous silicon systems. On site measurements for GHI, DHI and temperature as well as the AC output of the arrays were available for this analysis. Figure 6 also includes the statistical results for modelling hourly GHI in comparison to the measured values of global horizontal irradiance. Ignoring the results from the amorphous silicon (A-Si) system, the results again highlight a significant reduction in the overall level of uncertainty and bias when hourly GHI values of irradiance are available as input into the modelling process. The reduction in uncertainty observed for these systems in Alice Springs are on par with the reduction observed for the Nyngan system.

The high levels of bias and uncertainty observed for the A-Si system were found to be caused by the DC modelling algorithm that was incorporated within the initial version of Solar Analytics. The analysis of the DC algorithm revealed that the initial version of Solar Analytics was unable to model PV systems using amorphous silicon technologies. A new DC modelling algorithm was proposed that enabled modelling for all PV typologies.

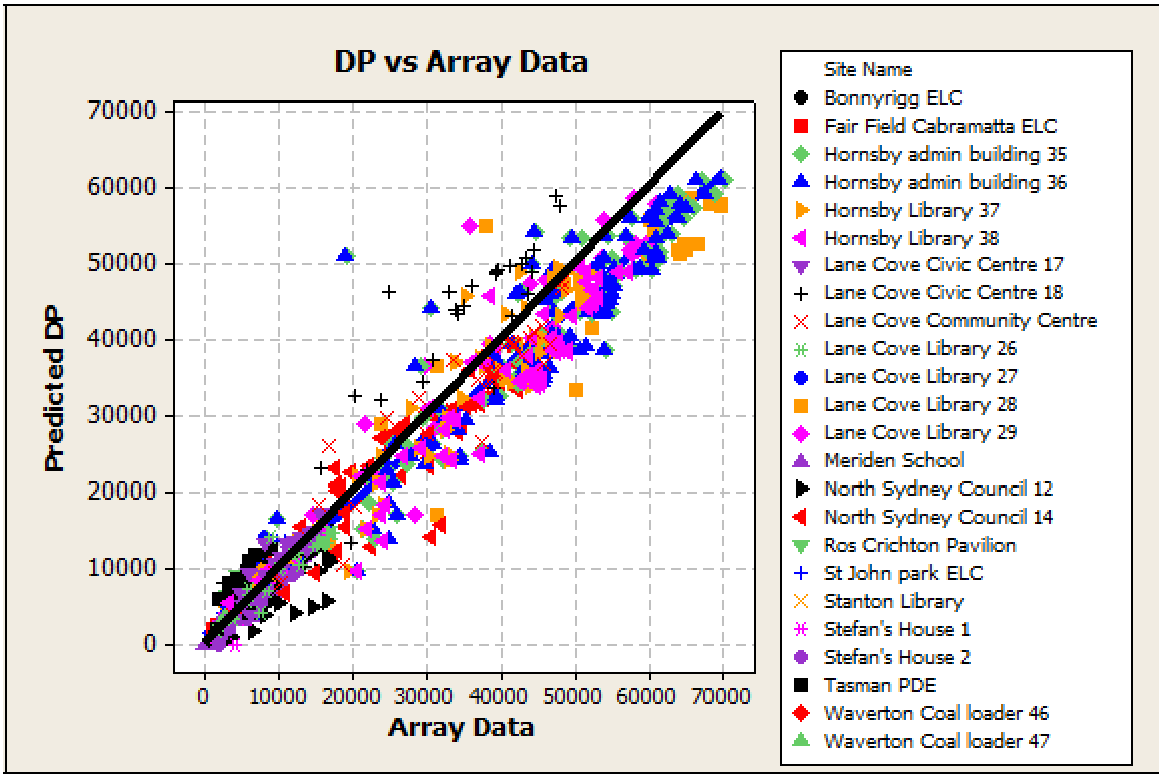


Figure 3 Scatterplot of daily predicted power from the DP version of Solar Analytics versus measured array data

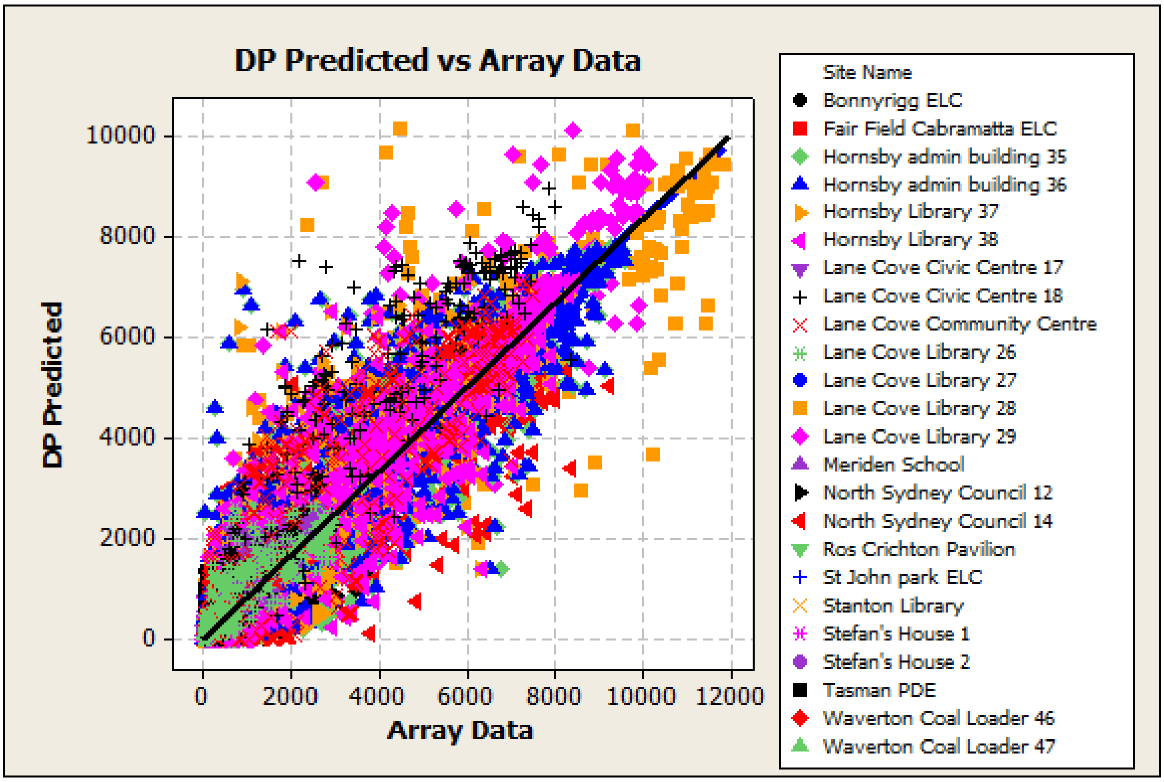


Figure 4 Scatterplot of hourly predicted power from the DP version of Solar Analytics versus measured array data

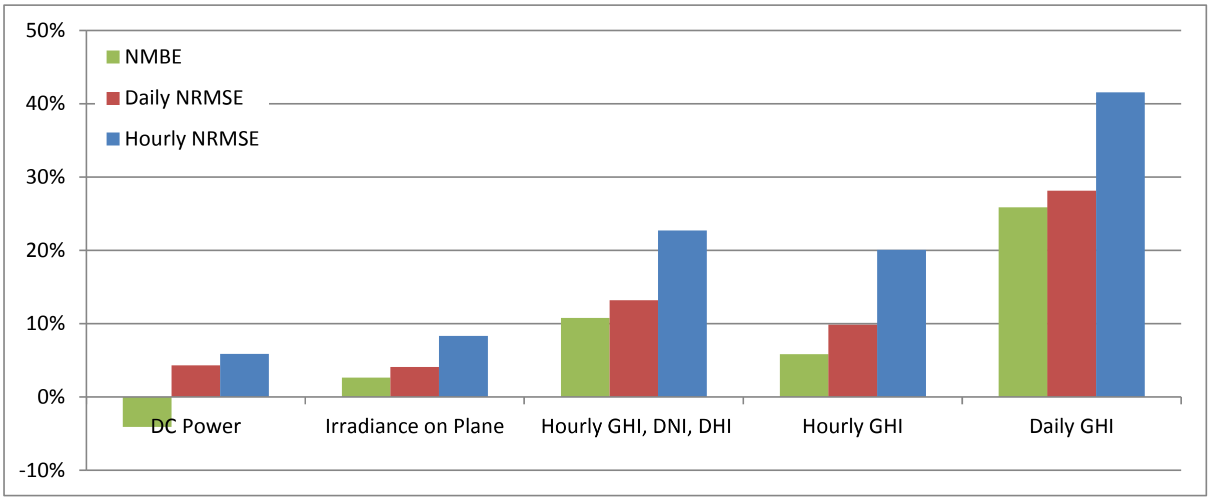


Figure 5 Normalised levels of bias (NMBE) and uncertainty (NRMSE) for AC predicted power versus array data plotted at each step of the modelling process. Labels discussed in the body of the text.

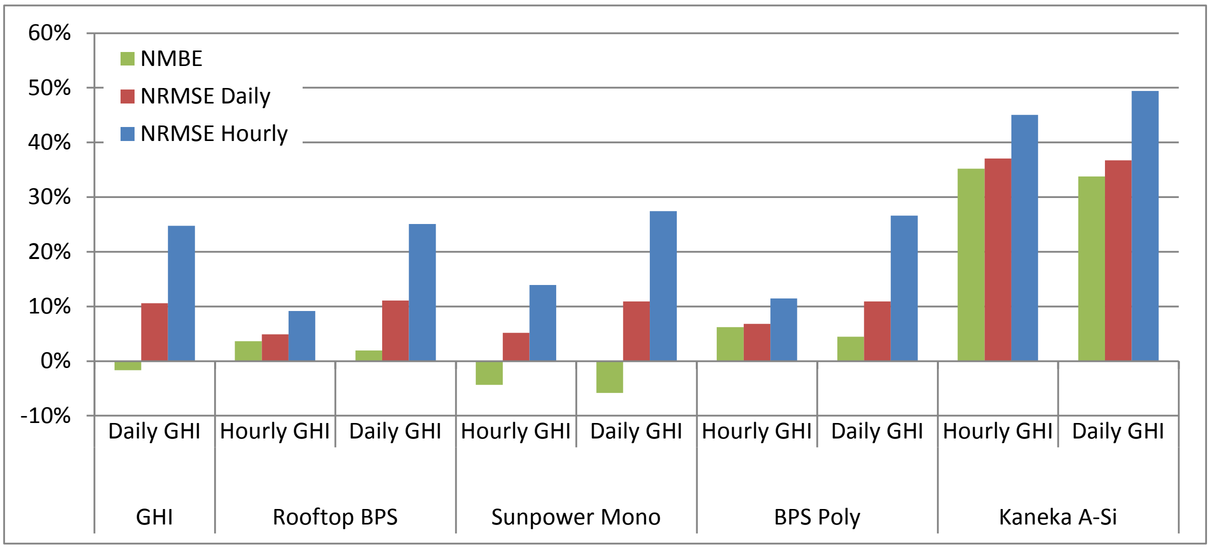


Figure 6 Normalised levels of bias (NMBE) and uncertainty (NRMSE) for AC predicted power versus array data from 4 PV systems located in Alice Sprints. The left most entry displays the statistics for modelling hourly GHI in comparison to measured values of GHI.

Modelling Results – Impact of modelling Irradiance

This section presents hourly PV performance modelling results using various inputs of plane of array (POA) irradiance in comparison to the measured AC performance of three PV systems located in the suburbs of Alexandria, Castle Hill and Kensington (UNSW). Details of the three PV systems are presented in Table 1. Onsite measurements of AC power from the inverter and POA irradiance, module temperature, ambient temperature and wind speed from SMA Sunny Sensor boxes were recorded in sub-hourly intervals at each location and converted into an hourly format. The array AC power and/or POA irradiance measured and recorded via the same methodology, for a number of PV systems located nearby to the three systems under analysis, were used as alternative data sources to estimate global horizontal irradiance (GHI) and POA irradiance. Details for the nearby systems are presented in Table 2. Measurements of meteorological parameters via SMA Sunny Sensor boxes and AC outputs as recorded via the inverter were deemed appropriate for the presented analysis as these two data sources are reflective of data availability for small scale PV systems within Australia.

Table 1: PV system parameters

	Alexandria	Castle Hill	UNSW
System size (kWp)	1.37	5.1	9.68
Module	7 x Suntech Power STP195S-24/Ad+	30 x Schott Solar GmbH POLY 170	42 x Suntech Power PLUTO215-Udm
Module technology	Monocrystalline	Multicrystalline	Multicrystalline
Inverter	1 x SMA SB1700	1 x SMA Sunny Boy 5000TL-20	1 x SMA STP12000TL
Tilt (°)	30	20	3
Orientation (0-360°)	37	35	9
Mounting	parallel roof mount	parallel roof mount	parallel roof mount
Type of Measurement	AC Power, POA & Module Temperature	AC Power, POA & Module Temperature	AC Power, POA & Module Temperature
Effected by Shading	No	No	No

Table 2: Nearby PV system or POA parameters

	Alexandria	Castle Hill	Lane Cove	Glebe	Kensington
System size (kWp)	1.39	5.1	9.6	NA	NA
Module	7 x Suntech Power HiPerforma 200-Ade	30 x Schott Solar GmbH POLY 170	48 x Suntech Power STP200-18-Ud	NA	NA
Module technology	Monocrystalline	Multicrystalline	Multicrystalline	NA	NA
Inverter	1 x SMA SB1700	1 x SMA Sunny Boy 5000TL-20	1 x SAM Sunny Tripower 10000TL-10	NA	NA
Tilt (°)	30	10	30	35	20
Orientation (0-360°)	37	35	356	15	6
Mounting	parallel roof mount	parallel roof mount	close roof mount	parallel roof mount	parallel roof mount
Type of Measurement	AC power	AC Power & POA	AC Power	POA	POA
Effected by Shading	No	No	No	No	No

For each of the three PV systems, seven POA irradiance modelling scenarios were investigated and are listed below:

1. Measured POA
2. Measured POA bias removed
3. Reversed POA to GHI
4. Clear Sky adjusted model
5. Gridded hourly GHI – BOM (satellite post processed)

6. Nearby POA to GHI
7. Nearby AC Power

The PV performance modelling of all 7 scenarios were identical except for the method used to estimate the POA irradiance. Onsite measurements of module temperature, measured via SMA Sunny Sensor boxes, were used as input into the PV performance model using the Sandia temperature model [29], with the open rack mounting configuration, to translate the measured module temperatures into cell temperatures. Hourly estimates of modelled AC power were calculated and compared to the measured AC response of the three PV systems for each of the 7 POA irradiance modelling scenarios. Results for mean bias deviation (MBD), root mean squared deviation (RMSD) and their normalised values were calculated based on the cleaned data sets for values of measured AC power greater than zero.

The statistics presented in Table 3, Table 4 and Table 5 describe the comparison between the measured and modelled quantities of AC power for the seven POA irradiance modelling scenarios for the locations of Alexandria, Castle Hill and Kensington (UNSW) respectively. The graphical results for the location of Alexandria are presented in Figure 3. Figure 3**Error! Reference source not found.** also plots the linear line of best fit as well as a line of one to one correlation for comparison.

Table 3: Mean AC power statistics for model estimates in comparison to measured AC power for the 1.37 kWp system in Alexandria.

	Measured POA	POA Bias Removed	Reversed POA to GHI	CSA
MBD - hourly (W)	-91.23	0.00	-6.04	-10.73
RMSD - hourly (W)	120.47	33.59	41.47	190.25
NMBD	-19.54%	0.00%	-1.29%	-2.24%
NRMSD (hourly)	25.80%	7.25%	8.84%	39.63%
NRMSD (daily)	21.63%	3.50%	4.35%	23.18%

	Hourly GHI - BOM	Nearby POA	Nearby AC Power 1	Nearby AC Power 2
Location		Glebe (2.97km)	Alexandria (0km)	Lane Cove (7.5km)
MBD - hourly (W)	-21.63	0.41	-10.70	1.43
RMSD - hourly (W)	144.96	89.58	38.36	120.82
NMBD	-4.22%	0.09%	-2.26%	0.30%
NRMSD (hourly)	28.31%	18.89%	8.10%	25.66%
NRMSD (daily)	13.01%	7.59%	4.03%	11.38%

Table 4: Mean AC power statistics for model estimates in comparison to measured AC power for the 5.1 kWp system in Castle Hill.

	Measured POA	POA Bias Removed	Reversed POA to GHI	CSA
MBD - hourly (W)	-533.71	0.00	-58.87	-41.15
RMSD - hourly (W)	630.66	190.35	201.32	639.83
NBMD	-27.76%	0.00%	-3.21%	-2.19%
NRMSD (hourly)	32.81%	10.28%	10.98%	34.10%
NRMSD (daily)	29.83%	5.22%	5.15%	19.07%

	Hourly GHI - BOM	Nearby POA	Nearby AC Power 1	Nearby AC Power 2
Location (Distance km)		Castle Hill (0.5km)	Castle Hill (0.5km)	Lane Cove (22.1km)
MBD - hourly (W)	-60.05	-76.29	-78.41	38.17
RMSD - hourly (W)	555.61	227.58	210.55	545.03
NBMD	-3.14%	-4.13%	-4.16%	2.02%
NRMSD (hourly)	29.08%	12.31%	11.17%	28.86%
NRMSD (daily)	10.05%	6.11%	5.55%	12.32%

Table 5: Mean AC power statistics for model estimates in comparison to measured AC power for 9.68 kWp system at UNSW

	Measured POA	POA Bias Removed	Reversed POA to GHI	CSA
MBD - hourly (W)	117.46	0.00	6.96	116.56
RMSD - hourly (W)	296.86	247.20	250.41	903.72
NMBD	4.16%	0.00%	0.24%	3.87%
NRMSD (hourly)	10.50%	8.74%	8.76%	30.03%
NRMSD (daily)	6.49%	5.55%	5.54%	17.55%
	Hourly GHI - BOM	Nearby POA	Nearby AC Power 1	Nearby AC Power 2
Location		Kensington (0.88km)	Alexandria (3.72km)	Lane Cove (9.46km)
MBD - hourly (W)	4.60	79.81	28.13	109.29
RMSD - hourly (W)	859.93	629.37	863.21	797.09
NMBD	0.15%	2.76%	1.08%	5.72%
NRMSD (hourly)	27.35%	21.75%	33.22%	41.70%
NRMSD (daily)	12.36%	9.82%	14.75%	17.50%

The results using onsite measurements of POA irradiance for the systems in Alexandria and Castle Hill indicate that the measurements of POA irradiance from the Sunny Sensor boxes contains a significant level of negative bias (-19.5% and -27.8% respectively), whilst only a small positive bias is noted for the UNSW system (4.2%). The removal of this bias demonstrates that the algorithms used to model the PV performance results in a low level of modelling uncertainty at both the hourly and daily levels for all three systems which would be appropriate for real time monitoring and fault detection of PV systems.

The reverse POA to GHI methodology, demonstrates an alternative method to correct for the bias within the measured POA irradiance data, which allows for a bias corrected calculation of AC power without prior knowledge of the measured system performance. This method estimates GHI from the measured POA irradiance data and then linearly adjusts the estimated GHI to the daily insolation reported by the Australian Bureau of Meteorology (BOM). The results from this scenario indicate a marginal increase in the level of modelling bias and uncertainty in comparison to the second scenario which was corrected for bias. The results also indicate a significant reduction in the level of bias and uncertainty of the POA to GHI scenario when compared to the first scenario which utilises the as measured POA data. Figure 3 which presents the graphical results for the system in Alexandria, demonstrates the reduction in modelling bias of the POA to GHI scenario in comparison to the first scenario utilising the as measured POA data. The figure also demonstrates the increase in modelling uncertainty attributed to using POA to GHI methodology

The worst PV performance results occurs for the fourth scenario where GHI irradiance was estimated via the ASHRAE clear sky model adjusted to the daily level of insolation reported from the BOM. It should be noted that this is the methodology that must be used in the absence of any measured data from either onsite or from a nearby location. This was the methodology employed in the initial version of Solar Analytics. The modelling results from the fourth scenario indicate a low level of bias (-2.2% to 3.5%) but a significantly high level of uncertainty at both the daily and hourly levels (17.6% to 23.2% at the daily level and 30% to 39.6% at the hourly level) which would not be appropriate for real time monitoring and fault detection of PV systems. The driver of the uncertainty for this scenario is the inability of the clear sky model to capture the variance observed in the irradiance measurements on cloudy and partially cloudy days.

The PV performance modelling results using the post processed hourly satellite derived GHI dataset from the Australian BOM, indicates a significant improvement in modelling uncertainty in comparison to the fourth scenario which utilised the daily level of insolation reported from the BOM. However, the level of uncertainty from this scenario is still more than double the level of uncertainty when onsite measurements of POA irradiance are available.

Increases in modelling uncertainty also occur for the final two scenarios where POA irradiance is estimated from either measured values of POA irradiance or AC power from systems at a nearby location. The modelling results presented in Table 3, Table 4 and Table 5 demonstrate that improvements in modelling uncertainty can occur from both of these scenarios in comparison to fourth and fifth scenarios if the location of the nearby PV system is within close proximity to the system under study. These differences can be observed in Figure 3. The daily level of uncertainty for the last two scenarios are on par with the daily level of uncertainty presented in [19] (15%) for PV modelling and monitoring using satellite derived irradiance data, which concluded that the uncertainty within the satellite derived irradiance data prevented the detection of small energy losses within the monitored PV systems but was able to diagnose significant faults like total blackouts and string outages.

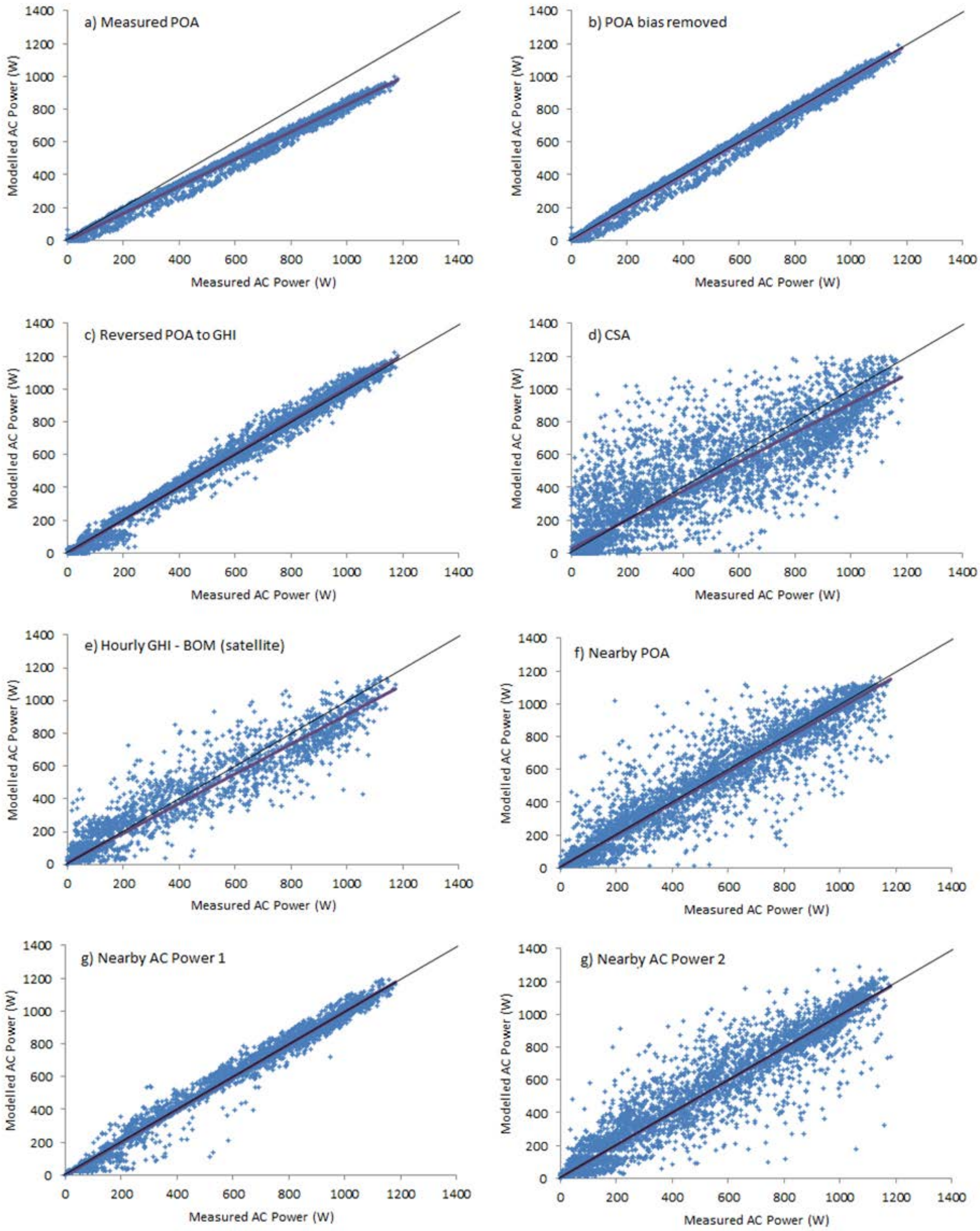


Figure 7 Measured versus modelled AC power using the different modelling inputs

The modelling results from the three PV systems investigated demonstrated that the simple PV performance model could estimate the AC performance of a PV system with a low level of model bias (3.2%) and uncertainty (<6% at the daily level) if onsite measurements of POA irradiance were available. In the absence of measured onsite POA irradiance the results indicated that modelling uncertainty increased significantly when alternative methods to estimate POA irradiance were used. The use of measured POA or AC power from a nearby PV system offered modelling advantages over the hourly gridded satellite derived irradiance dataset from the BOM, if the location of the nearby PV system was in close proximity to the PV system under study.

Performance Monitoring

A number of potential performance monitoring schemes were developed which may provide Solar Analytics with the opportunity to not only monitor the performance of PV systems but help identify when PV systems are underperforming and the cause of the underperformance. Suntech provided a list of typical faults, which were used to help develop the diagnostic algorithms and performance monitoring schemes. A detailed report detailing the algorithms and schemes were provided to Suntech.

Unfortunately due to the lack of measured PV system data with faults, the schemes and algorithms provided are only the initial phase of developing a robust diagnostic capability. Testing of these initial algorithms and further refinement of the algorithms were recommended.

Figure 8 and Figure 9 provide schematics of the process flow recommended for use within Solar Analytics for performance monitoring. The strategy provided can make use of any performance metric like the performance ratio (PR), PV system efficiency (ηPV) or the ratio of measured to estimated AC power (MER). The MER is however the recommend metric for use in Solar Analytics as the performance limits are easily defined by the error (uncertainty) of the modelled estimate. The provided strategy categorises any observed underperformance into one of four warnings. These warnings are then used to determine when the performance diagnostic algorithms should be run. The performance diagnostics are not run as soon as any underperformance is observed to prevent false diagnosis of an error.

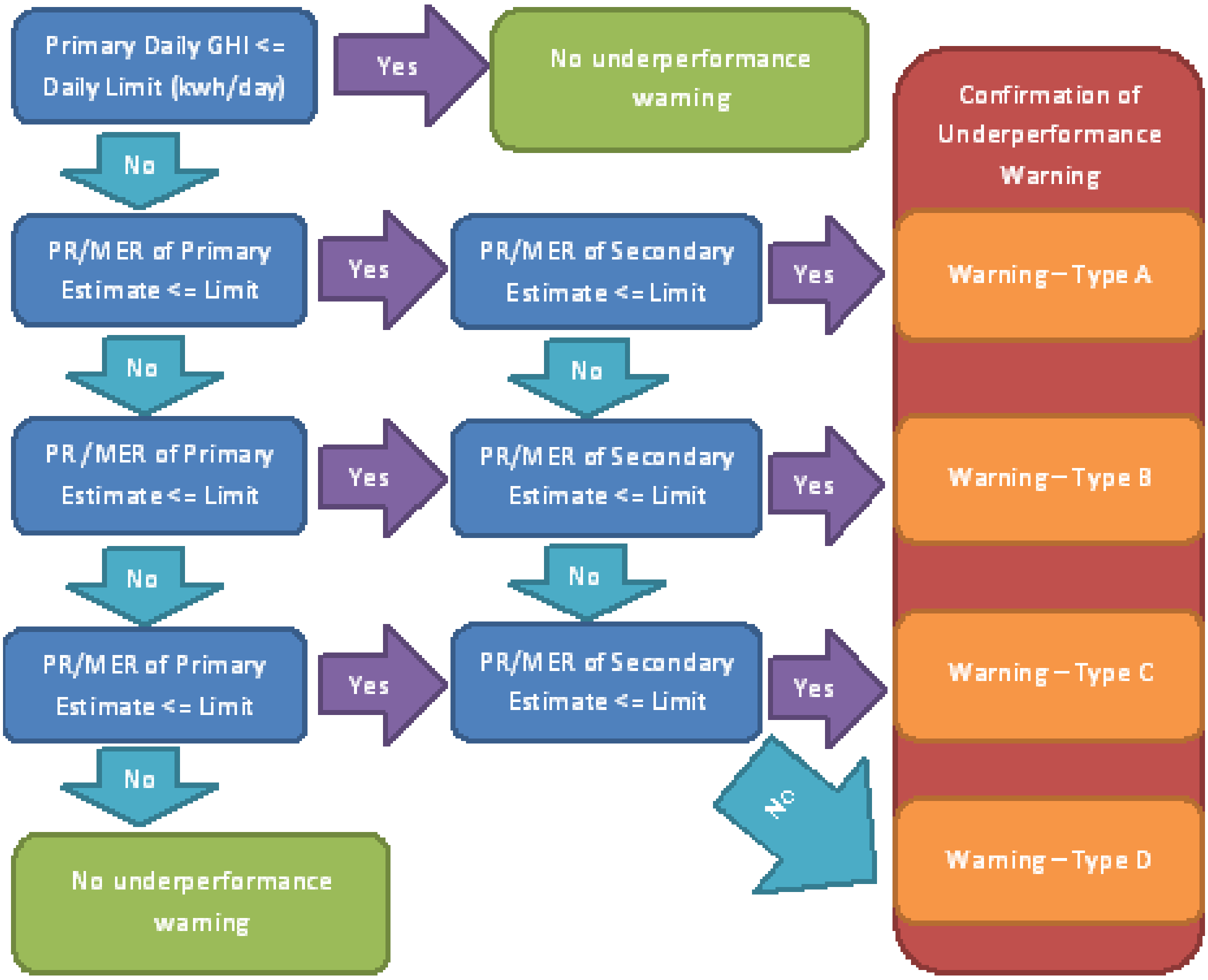


Figure 8 Process flow for diagnosis of underperformance based on the daily level

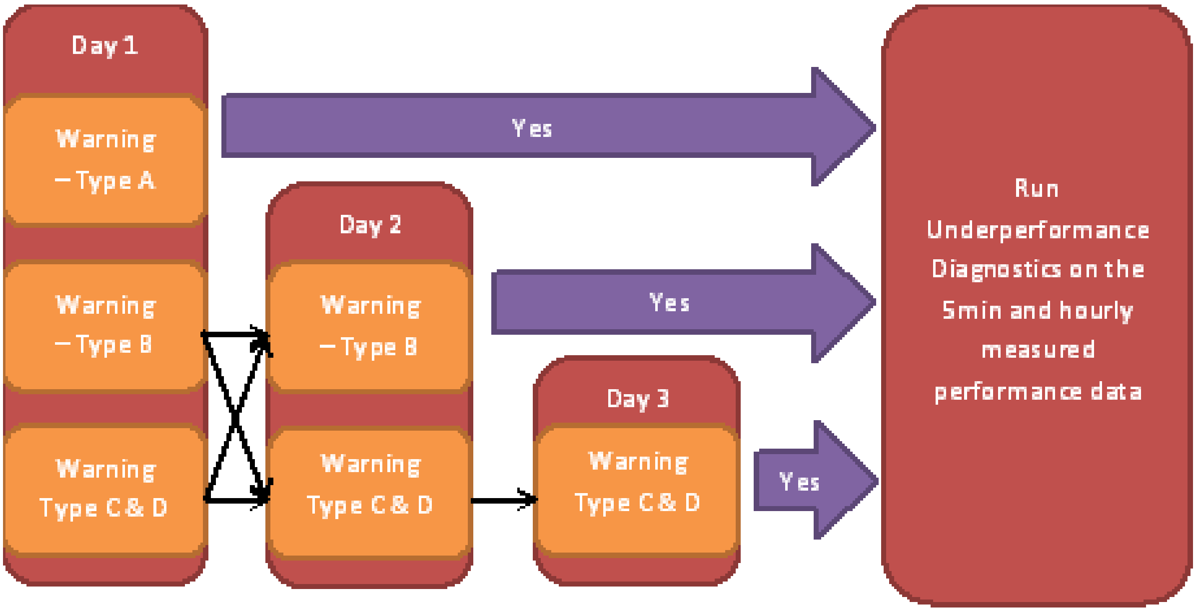


Figure 9 Process flow to initiate underperformance diagnostics

Building Energy Monitoring Management

The feasibility study into the demand for and viability of a similar modelling approach for the monitoring of energy consumption in commercial buildings is summarised below. It involved a review of current building energy monitoring requirements, programs and products in the market.

The study focussed on Class 5 Commercial Office buildings with a net lettable area (NLA) between 500 and 2500m2. This NLA range reflects the size of C, D and smaller B grade buildings. The maximum NLA limit also corresponds with the limit stated by the Building Code of Australia (BCA) 2013, where the installation of sub-metering is not required for compliance. The BCA 2013 only requires all new or modified parts of Australian buildings “with a floor area of more than 500m2 must have the facility” to record the consumption of gas and electricity. Buildings of this size generally have external facility management providers with limited time or incentive to propose and implement energy reducing initiatives.

The National Australian Built Environment Rating System (NABERS) Office Energy provides a yearly rating for a building or tenancy, from 0 to 6 Stars, and as such does not provide the required daily, weekly or monthly resolution required of this project. NABERS is an important part of the Australian commercial property market as it is widely used in national programs including the Commercial Building Disclosure legislation, Property Council of Australia’s Guide to Office Building Quality 2012 and Green Star rating tools.

NABERS has the largest data base of annual energy use in office buildings and allows the NABERS Energy star rating to be used to fairly compare buildings to each other. To predict a NABERS Energy rating, requires simulating the building’s annual energy performance based on mechanical, hydraulic, electrical equipment power ratings, expected run-times, expected occupancy numbers and hours etc.

There are only a few commercially available “active” energy management systems that have similarities to Solar Analytics. These include:

- Green Buildings Alive
- OPower

Neither of these systems provides simple corrective action feedback of the kind considered by this project. From this desktop study, a product that can both predict daily energy performance against actual daily performance and provide corrective actions similar to Solar Analytics was not identified. The currently viable method is contracting consulting services to predict annual energy performance, monitor and provide specific recommended actions.

Dynamic simulations of buildings to predict the energy performance of a building are usually based on a standard real weather data set such as the Test Reference Year (TRY) files or International Weather for Energy Calculation (IWEC) files. Current simulation software cannot process or format current weather data from the Bureau of Meteorology and re-run the simulation in order to predict the last day’s energy performance and compare against actual energy use. For Green Buildings Alive and Opower, comparisons have been made from their database of real electricity data for similar weather and building conditions.

As for generating corrective actions, in the building industry there are generally three levels of recommended actions from general to specific. This includes the freely available standard audit check list or generic energy efficiency initiatives list, anomaly reporting from the data and contracting human services to model and monitor at least a month of historical data to recommend specific actions. For this CRC project, the effectiveness and availability of these recommended actions will have an effect on the market potential of such a system.

The corrective actions are likely to be generic from an automated system if it is applied to all ages of buildings for two reasons. Firstly, the automated system would need to account for buildings of different ages that will have different levels of sub-metering. In general, older buildings may only have one single utility meter, which the utility collects the data from on a monthly basis. This data is not always able to be collected automatically nor at the frequency suggested for energy analysis. Newer buildings may have sub-meters installed however, the data is not collected manually or there is no system to automatically collect the data.

Secondly, analysis of data to provide meaningful outcomes is not a simple process. Lower levels of sub-metering increases the difficulty to provide meaningful energy reducing recommendations. For a building with a single meter that collects 15 minute electricity data, it is very difficult to identify which of the many sub-systems are underperforming. There is limited resolution of the potential breakdown of energy consumers.

Determining the daily energy performance of a building is valuable to building managers and owners. It has market value for small-medium commercial sized office buildings where building managers are incentivised by the building owner to use this information to reduce energy consumption. However the generic corrective actions that are likely to be generated from such an automated system have little value due to its likely free availability.

PV System Performance Forecasting

Plane of array (POA) irradiance is the most influential parameter on the performance of a PV system. Hence POA irradiance is the most important parameter that needs to be estimated for PV power forecasts. Estimates of wind speed and ambient temperature are also required but have less of an influence. The review undertaken for this CRC project focused solely on the ability to forecast irradiance.

A review of the literature indicated that three primary methodologies exist for forecasting global horizontal irradiance (GHI) which can be used with standard methodologies to estimate POA irradiance. The irradiance forecasting method chosen is dependent on the time scale of the required horizon forecast. The three irradiance forecasting methods based on the time scale of the horizon forecast summarised in [30, 31] as:

- Very short term forecasts ranging from minutes to a few hours.
  - Forecasts of irradiance typically undertaken via the use of on-site measured irradiance and/or other meteorological parameters in combination with time series models.
  - Examples of time series models used for short term forecasts in the literature include Kalman filtering, autoregressive (AR), autoregressive moving average (ARMA) and artificial neural networks (ANNs).
- Short term forecasts ranging from a few hours up to 6 hours ahead.
  - Forecasts of irradiance typically undertaken via information on the temporal development of cloud cover.
  - Forecasts based on satellite images have shown good performance for up to 6 hours ahead.
  - For sub hour range, cloud information from ground based sky imagers have been used to derive irradiance forecasts with much higher spatial and temporal resolution compared with satellite based forecasts. Forecasts horizons for this method are limited by the spatial extension of the monitored cloud scenes and corresponding cloud vectors.
- Longer term forecasts from about 4-6 hours onward.
  - Forecasts of irradiance typically based on numerical weather prediction (NWP) models. These models have typically outperformed satellite based forecasts for longer forecast horizons.
  - Some weather services, for example, the European Centre for Medium Range Weather Forecasts, directly provide surface solar irradiance as forecast model output.
  - However, surface solar irradiance is still mot a standard prediction variable of all weather services. In such a scenario statistical models may be applied to derive irradiance from available NWP output variables and to adjust irradiance forecasts to ground measured or satellite derived irradiance data.

Two figures were presented in [31] to explain the relationship between the three forecasting methodologies listed and how they relate to spatial resolution, forecast horizon and forecasting need. These figures are reproduced in Figure 4 and Figure 5. The figures highlight that the choice of forecasting methodology also needs to be determined based on the use of the forecasted data.

Based on the data Solar Analytics is currently collecting and the processing and computational requirements of the three forecasting methodologies, the short term up to 6 hours ahead forecast of irradiance via the use of either time series modelling or sky imaging methods may be possible. The satellite imagery method is ruled out due to high computational requirements and access to data. The drawbacks of the methodologies compatible for potential integration into Solar Analytics are that they have low spatial resolution.

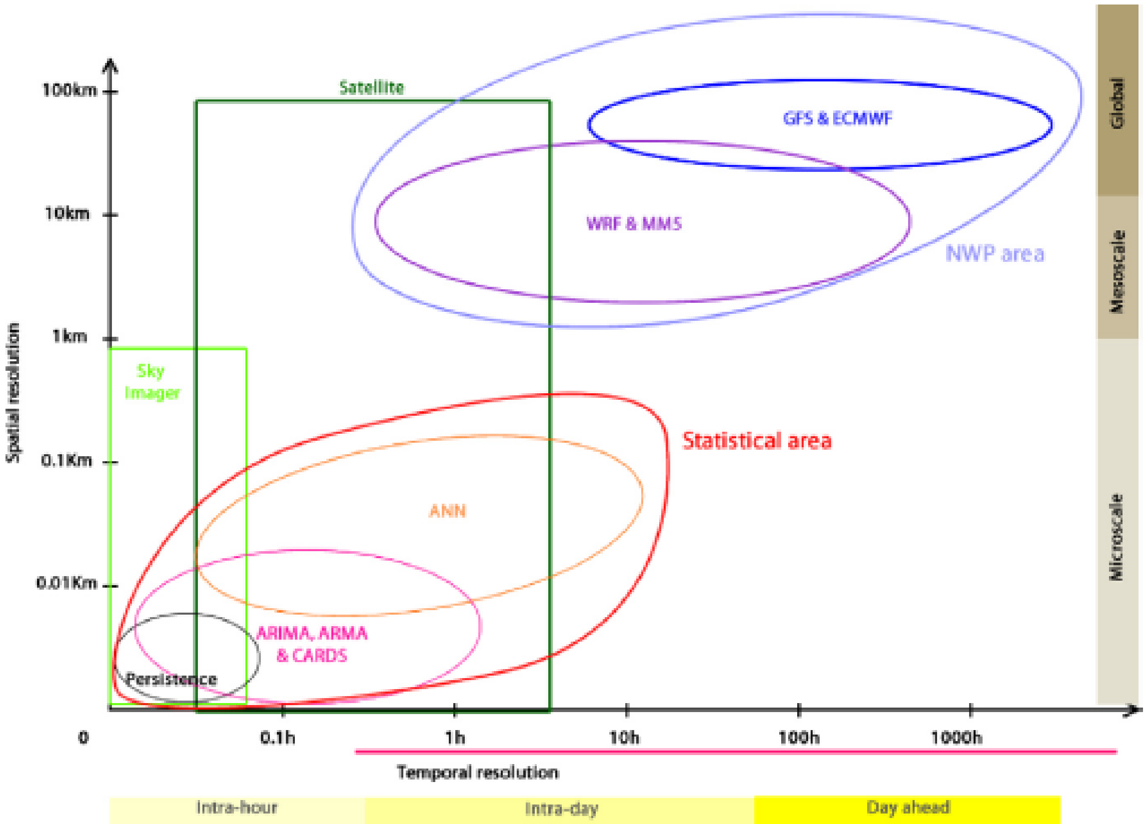


Figure 10 Classification of model based on spatial and temporal resolution (Fig 4 [31])

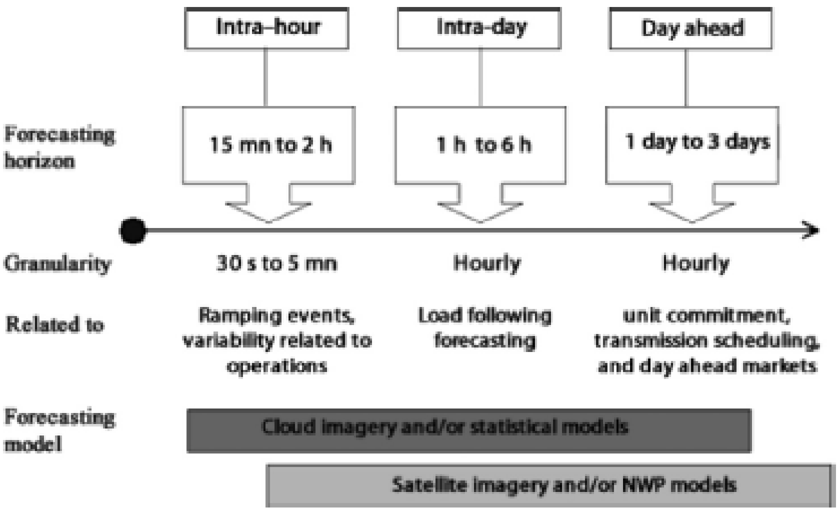


Figure 11 Relation between horizons, models and activities (Fig 5 [31])

Research presented in [32] provides a demonstration of the type of forecasting that is possible for integration within Solar Analytics. The forecasting example presented in [32] used the power output from 80 rooftop PV systems distributed across a 50km x 50km area to forecast PV output for forecast horizons between 30s to 6 hours. Figure 6 and Figure 7 reproduce results presented in [32], demonstrating the ability of the sky imaging methodology over short (30-45min) forecast horizons. Figure 3 demonstrates the power output for each of the 80 systems at three different times. The dark points (indicating low output due to cloud coverage) shift from southeast towards the northwest over the course of the hour demonstrating the ability of the methodology to map the path of the cloud coverage. In this example the average spacing between systems was 3km, providing measurements every 15 minutes. Figure 7 in contrast provides a direct example of the forecasted PV output in comparison to a persistence model forecast, the clear sky reference and the actual measured profile of the system under study. The results indicate a reasonable agreement between the 45min forecast and the measured PV performance. The results also demonstrate an improvement in the forecast results over the persistence model.

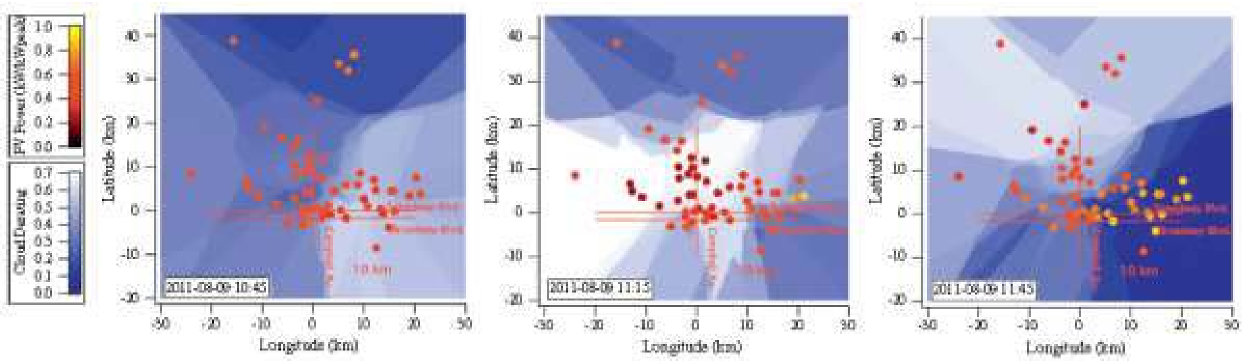


Figure 12 Measured PV output at three times separated by 30 mins. Background colour is the interpolate clearness index (K), white areas are cloudy, blue areas are clear (Fig 1 [32])

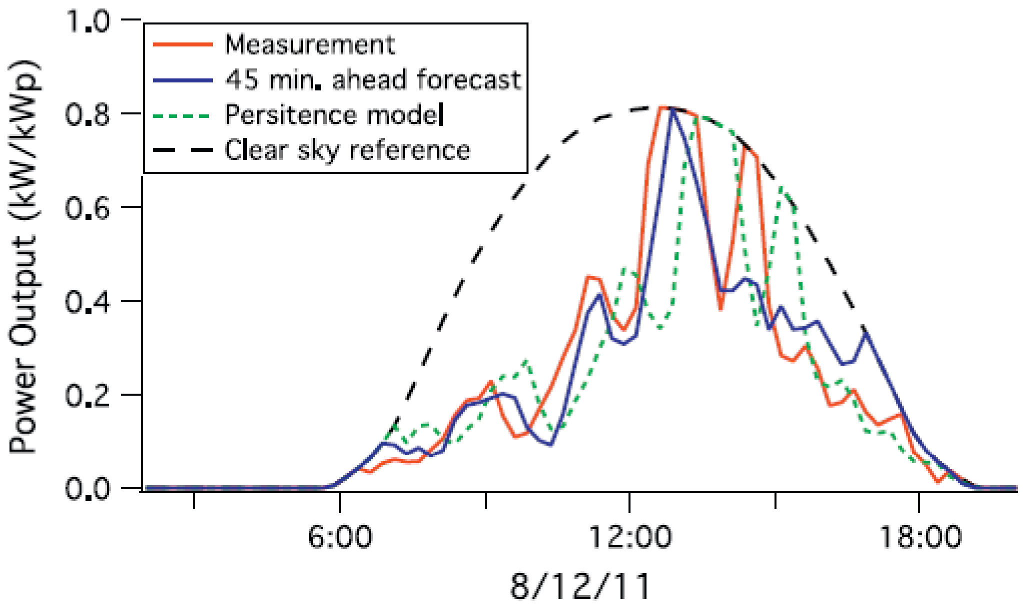


Figure 13: Measurement and 45 min ahead forecast of PV performance using a network of 80 PV systems, presented in comparison to persistence model and clear sky model results. (Fig 2. [32])

Conclusions

This CRC project successfully assessed and improved the algorithms used within the initial version of Solar Analytics provided by Suntech R&D Australia. The performance assessment of the initial version of Solar Analytics revealed that the algorithms that constituted Solar Analytics were unable to handle PV systems with modules of various typologies, orientations and tilt angles. Similarly the assessment revealed that the DC algorithm used was unable to handle PV systems of amorphous silicon technology. The overall assessment of Solar Analytics ability to estimate AC power indicated that the initial version of Solar Analytics modelled the performance of 17 PV systems with average levels of bias and uncertainty of -7% and 22% respectively. The algorithm used to estimate hourly GHI was determined to contribute more than 50% of the observed level of uncertainty. As a result of the initial performance assessment of Solar Analytics, alternative modelling algorithms were suggested and integrated within the program to resolved the aforementioned issues and also covered other modelling issues like self-shading, shading from fixed elements and degradation of system performance with age.

Testing of the refined algorithms, integrated within the new version of Solar Analytics, revealed that when onsite measurements of POA irradiance were available, Solar Analytics could estimate the AC performance of the PV systems with levels of bias and uncertainty below 3% and 6% respectively at the daily level. In the absence of measured POA irradiance the results indicated that modelling uncertainty increased significantly when alternative methods to estimate POA irradiance were used. The analysis also highlighted that POA irradiance estimated via the use of measured POA or AC power from a nearby PV system offered modelling advantages over the post processed hourly gridded satellite derived irradiance dataset from the Australian Bureau of Meteorology (BOM), if the location of the nearby PV system was in close proximity to the PV system under study.

This CRC project also developed an initial set of diagnostic algorithms and monitoring processes that could be incorporated within Solar Analytics to help diagnose PV system faults at the earliest possible stage. The proposed schemes would enable Solar Analytics the ability to diagnose zero AC power faults, shading due to fixed elements like buildings or trees (when shading had not been previously assessed, measured and incorporated within the modelling estimate), string faults and potential induced degradation (PID) faults. Unfortunately due to the lack of measured PV system data with faults, the schemes and algorithms provided were only the initial phase of developing a robust diagnostic capability. Testing of these initial algorithms and further refinement of the algorithms are recommended as further work.

This CRC project also undertook a surface review of irradiance forecasting techniques to determine whether forecasts of PV system performance could be incorporated within Solar Analytics at some point in the future. The review indicated that very short to short term irradiance forecasting methods maybe applicable for integration within Solar Analytics. However the business case for forecasting PV performance and its integration with Solar Analytics needs to be justified before it is recommended that further time and effort be spent furthering this topic.

This CRC project also successfully completed a feasibility study into commercial building energy management systems and their potential integration with PV system prediction algorithms to create a simple and holistic energy management platform for the small-medium sized commercial buildings market. The study found that understanding the energy performance of the building compared with itself or other buildings is important due to large support for NABERS Energy nationwide. It was also found that corrective actions automatically generated from a system similar to Solar Analytics is likely to be generic and of little value in the market as it is freely available.

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