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Short term variability of utility-scale PV in the Australian National Electricity Market

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Abstract

Increasing penetrations of utility-scale PV introduce more operational uncertainty to power systems, as it firstly creates more short-term imbalance between demand and supply due to the variable and only partially predictable behaviour of PV over short time frames, and secondly displaces conventional generation which traditionally assists in managing system imbalance and provides inertia to resist short-term frequency deviations. In the Australian electricity market, frequency control ancillary services (FCAS) are used to purchase regulation services to correct short-term uncertainty within the 5-minute dispatch period, and contingency services to correct manage sudden unexpected changes in demand or supply. However, it is unclear if and how these arrangements might need to change with more PV. One risk is that penetrations of PV might be unnecessarily unlimited given the present uncertainties of its impacts.

This paper seeks to address some of these questions by analysing the short-term operational characteristics of utility-scale PV in the Australian National Electricity Market, at the timescale of seconds. Several studies have been carried out to understand the short-term characteristics of PV output, including the magnitude and frequency of output fluctuations and ramp rates over different timescales in different regions. However, the limited availability of high resolution data for utility-scale PV has hampered such work.

Our study analyses four second-resolution output from four utility-scale PV plants (20 MW – 100 MW) that are registered generators in the Australian National Electricity Market (NEM). The statistical analysis examines the significance of PV output fluctuations at this 4-second timescale. The results show that the variability over a four second time interval is insignificant, but that extreme events, with ramp rates of the size of the entire utility PV plant, potentially sufficient to trigger frequency regulation and contingency services, do occur albeit infrequently. These events are much more likely to be caused by operation issues rather than cloud transients, a challenge shared by conventional generation which is also subject to sudden unexpected forced outages. Although the current level of PV penetration in the NEM is low such that the impacts are barely visible, the variability of combined PV plants suggests that there is more frequency occurrence of large magnitude change in aggregated PV power output. This study represents the first stage of work assessing the scale of the variability challenge imposed by utility PV, and hence appropriate management options.

1. Introduction

The increasing penetration of utility-scale photovoltaic (PV) generation in electricity industries around the world is assisting in reducing the sector's environmental harms but does introduce a number of challenges for power system operation. Available PV generation from such plant is inherently highly variable and only partially predictable over all relevant time periods of operational decision making. This adds to the challenge of maintaining supply-demand balance at all times and locations across the network. Furthermore, these plants displace conventional generation which typically has greater dispatchability to assist in managing variability in both demand and other generation. And of particular relevance to short-term frequency management, the power electronics interface of PV does not offer the inertia of conventional plant with synchronous generators, that inherently and immediately acts to resist frequency deviations (AEMO, 2015).

Electricity market arrangements already require a range of ancillary services to assist in short-term frequency management given the variability and only limited predictability of energy demand (regulation), and major disturbances arising from the unexpected failure of large conventional generation or network elements (contingencies). However, utility PV has novel characteristics that are not yet fully understood and, hence, there are growing efforts to better understand the variability and uncertainty of such plants, and explore revised market arrangements to assist in managing this. One approach already in use for wind generation in a number of electricity industries is to set a minimum synchronous generation requirement for market dispatch. This inherently limits the instantaneous proportion of generation arising from variable renewables. Such arrangements can, of course, have adverse impacts on the dispatch and revenue of renewables generators and raises questions of how these limits should be set, and whether other management approaches might be more appropriate.

These questions provide the motivation for the study presented in this paper. In particular, the variability of utility PV is still only partially understood. This variability can also be expected to vary according to the location (e.g. micro-climate) and chosen technologies (e.g. fixed plate versus tracking) of the plants. Several studies (Curtright and Apt, 2008; Mills *et al.*, 2011; Sayeef *et al.*, 2012; Shedd *et al.*, 2012; Heslop and MacGill, 2014; Bucciarelli *et al.*, 2015) have been carried out to understand the short-term characteristics of PV output, including the magnitude and frequency of output fluctuations and ramp rates over different timescales in different regions.

There is considerable historical data available for large utility scale PV generation over typical time frames of wholesale market operation (5-30 minutes). There are also some data sets of high temporal resolution (seconds) PV generation for particular, generally small to medium size, PV plants. However, there is currently only very limited data from large utility size plants over the very short time frames relevant to frequency control ancillary services (FCAS). For example, the Australian National Electricity Market (NEM) operates regulation and fast contingency services at available SCADA (four seconds) time intervals, up to the five minute period of spot market dispatch. The limited availability of high resolution data for utility-scale PV has limited the usefulness of variability assessments.

The FCAS markets in the Australian NEM actually provide the basis for this work, as they provide public four second generation output data for all scheduled generating units as part of their calculation of how much each participant should pay for these services.

In order to better understand the variability of utility-scale PV, this paper analyses four second-resolution output from the first four utility-scale PV plants (20MW – 100MW) in the NEM. Variability here is specifically defined as the change in power output over time (Ela *et al.*, 2013; Riesz and Milligan, 2015).

As far as we are aware, this study presents the first analysis of this four second data for four utility PV plants currently operatin**g** in the NEM. Statistical analysis is undertaken to examine the significance of PV output fluctuations at the 4-second timescale.

A description of the datasets and methodology used for the analysis is presented in Section 2. Section 3 and Section 4 describes the outcomes of the variability analysis and the interpretation of the results including the investigation of extreme ramp events. Section 5 presents some preliminary conclusions of the study and directions for future work.

2. Methodology

The instantaneous power output at 4-second intervals of four utility-scale (20-102MW) PV plants in Australia was extracted from the AEMO Ancillary Services Market Causer Pays Data which is publicly available from the AEMO website (AEMO, 2016). A summary of the utility PV plants, size, capacity factor, technology and time period of available data analysed in this paper is presented in Table 1.

Table 1. Existing PV plants with AEMO 4-second ouput (causer pays) data available

Plant (latitude, longitude)	AC Capacity (MW)	Capacity Factor (as of 2016)	Data available from	Mounting Technology
Nyngan, NSW (-31.57, 147.08)	102	25%	May, 2015	Fixed-tilt
Moree, NSW (-29.57, 149.87)	56	26%	February, 2016	Single-axis tracking
Broken Hill, NSW (-31.99, 141.39)	53	22%	August, 2015	Fixed-tilt
Royalla, NSW* (-35.49, 149.14)	20	22%	April, 2016	Fixed-tilt

* Non-scheduled generator

2.1. Data cleaning

Statistical analysis was limited to daylight hours between sunrise and sunset. Therefore, the number of data points on each day for each individual PV plant is different (different starting timestamp and ending timestamp). In practice, there can be some complexities in analysis at the start and end of days depending on the plant configuration, weather conditions and inverter characteristics. For a comparative analysis, all the datasets must be time synchronised. To achieve this, any missing data for a particular timestamp was filled by assuming the value of the previous timestamp. Long periods of missing data were not observed in these datasets. However, the dataset did include days where communication errors were observed, such as a day that showed power output at one plant continue until 9PM, and these days were discarded from the analysis.

2.2. Variability

Variability here is defined as the change in PV plant power output over time. Variability of PV generators was therefore calculated from the difference between the instantaneous power at the next time frame and the current time frame as shown in Equation 1.

$$Variability(t) = P(t+1) - P(t) \tag{1}$$

Where P(t) is the power output recorded at timestamp (t) and (t + 1) is the next timestamp. The sampling frequency of power output, and hence shortest timeframe for variability analysis, was 4 seconds, which is the SCADA time period for NEM operation.

2.3. Categorisation of sunny and cloudy days

In order to explore the variability observed under different general weather conditions, the analysis established sunny and cloudy day categories. It has also sought to identify periods where the plant output was likely being impacted by operational issues such as partial or complete forced outages, or curtailment requirements. In previous studies, categorising sunny and cloudy days has done by using solar resource data to create clear sky profiles and comparison of the output from PV plants with the clear sky profile (Ibanez *et al.*, 2012; Gibescu, Nijhuis and Rawn, 2014). In the absence of solar resource data, categorisation for this study is done by analysing the output fluctuation of the PV plants. Haghdadi et al. (2017) proposed a method for classifying clear sky periods by discarding all periods which exceed the aggregated variability threshold over a period (e.g. 1 minute) to achieve such categorisation. The clear sky periods were retained and fitted with 3rd degree polynomial equations to create a clear sky profile for each day. The study used several years of PV output data in order to establish the profile, which could then be compared to the output data as a basis for accurately determining cloudy periods in the data. However, while 3rd degree polynomial equations can be fitted to the daily output of fixed PV arrays such as those studied by Haghdadi, Figures 1-2, they cannot be applied to the generation profile from a single-axis tracking system, Figure 3. Another approach is to categorise the data by aggregated ramp rates over the whole day, as proposed by van Haaren et al. (2014). Although solar irradiance is used by van Haaren et al. to calculate variability, this method does not rely on the sky clearness index and therefore the plant power output can also be used. One drawback of this method is that it cannot distinguish between clear sky and completely overcast days as the aggregated variability of both days are similar yet the magnitude of power output would be different. Therefore, sub criteria must be applied.

In this paper, we adopted the van Haaren method to classify the operational characteristics of the PV plants, with the addition of sub criteria. Two factors were considered in the classification, (1) the aggregated variability over the whole day, normalised to the plant capacity and (2) the average power output between 10AM to 2PM, when the output of the plants will be typically relatively stable with regard to changes in the sun's position, normalised to the plant capacity. The analysis also established criteria for detecting days with operational issues such as plant failure or perhaps market dispatch instructions. The criteria are presented in Table 2. The results are shown in Figure 1 to Figure 3 for the three larger PV plants. It is interesting to note that the curtailed output at Nyngan is often around 50% of the plant capacity (Figure 1). The curtailed output from Moree also shows the same pattern (Figure 3) whereas the curtailment at Broken Hill appears to have three steps of 25% of the plant capacity (Figure 2). These are likely to outcome of inverter, wiring or network connection configuration of the plants. Significant clipping during the middle of sunny days is apparent at the three larger plants, suggestive of a significant DC/AC rating ratio.

Table 2. Criteria to categorise types of day

Category - Label	Description	Normalised daily aggregated variability	Normalised average power output between 10AM - 2PM
Category 1 - ClearSky	Clear sky	<= 3	>= 0.7
Category 2 - Curtailed**	Output is clipped or curtailed	<= 6	0.4 <= x <0.7
Category 3 - OpIssue	Operation issue (operating at very low output)	<= 3	<= 0.1
Category 4 – PartlyCloudy	Partly cloudy	3 < x <= 6	>= 0.7
Category 5 – Overcast	Cloudy/overcast	3 < x <= 6	< 0.4
Category 6 - ScatteredCloud	Scattered moving clouds resulting in high fluctuation of solar irradiation.	> 6	No limit

** An additional criteria was added to Category 2 to distinguish between cloudy days when the output fluctuated but still resulted in the same average power output as the day with curtailment. This is to consider the 90th percentile of the power output throughout the day. If the 90th percentile of the day falls below the threshold, the day is discard and classified as Category 5. The threshold was determined from 90th percentile value of day that the output of the plant was curtailed. The day with curtailment was observed by visual inspection. Note that the level of plant curtailment is different from plant to plant.

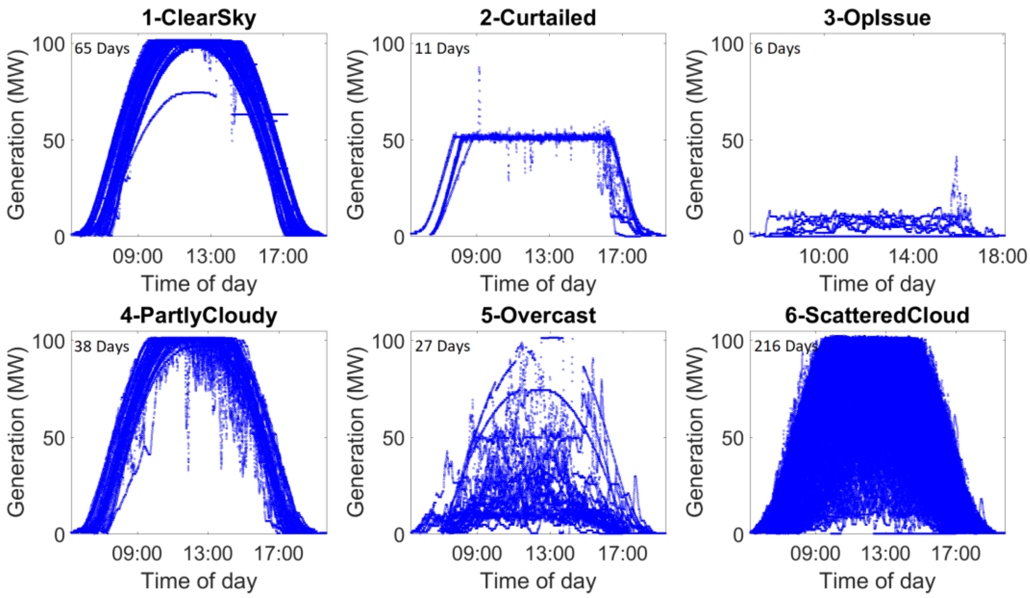

Figure 1. Nyngan power output profiles in 2016

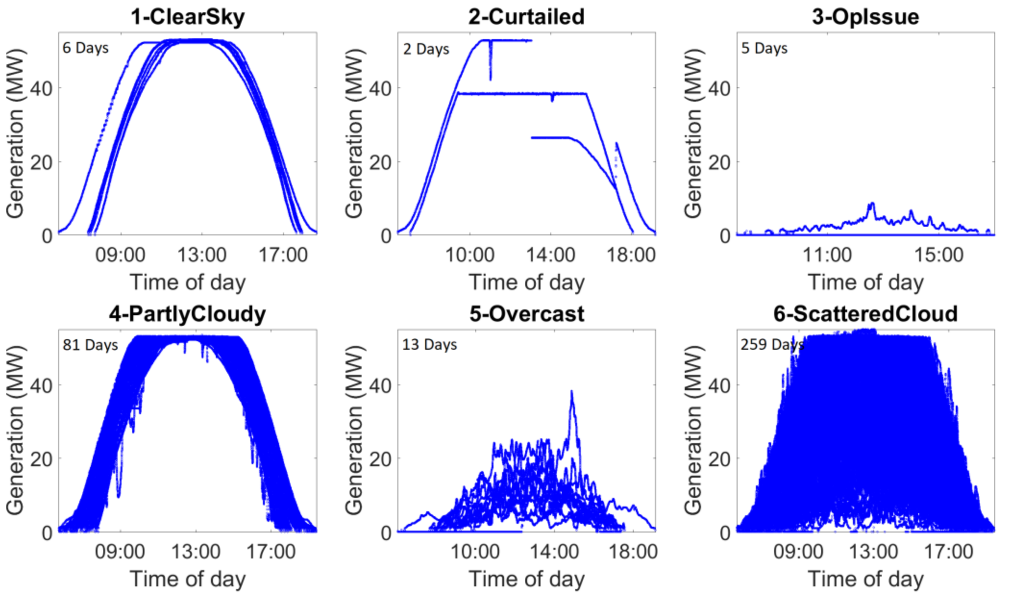

Figure 2. Broken Hill power output profiles in 2016

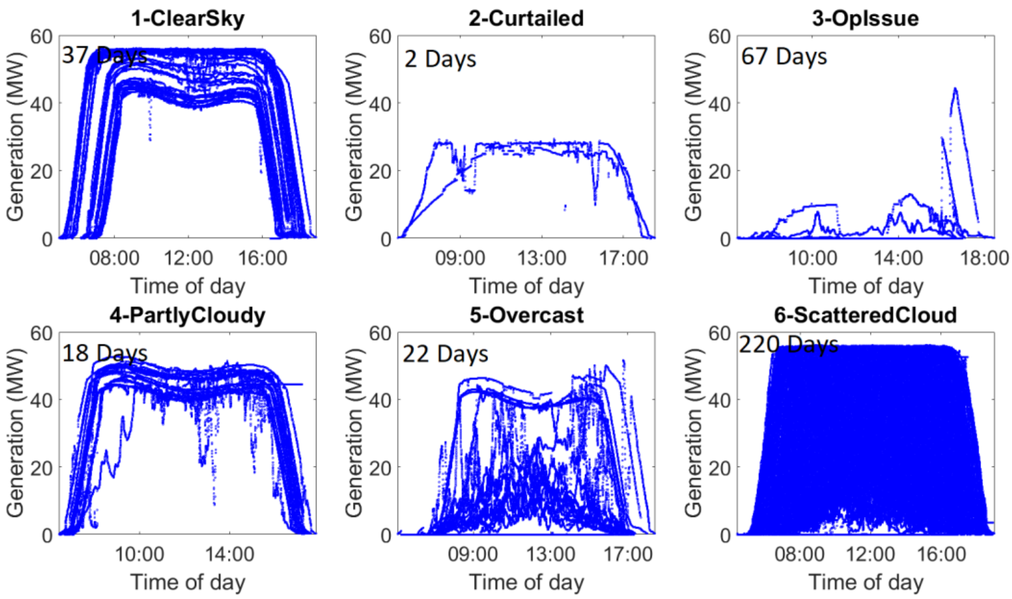

Figure 3. Moree power output profiles in 2016

3. Variability analysis

3.1. Variability of individual PV plants

The results from the analysis of the variability over 4 seconds of the output at PV farms in Australia in 2016 are shown in Table 3. Normalised change in power output per unit is a common way to present output variability and allow comparison to be made across different plant sizes. However, normalised ramp decreases as the plant capacity increases. As this study focus on the magnitude of change in power, presenting the normalised ramp could be misleading. Changes in power output over 4 seconds in this study were therefore presented as absolute magnitudes (MW) to demonstrate the potential impacts of PV variability on the system. Table 3 shows that the output variability from all individual PV plants remains within 1MW over 95% of the time. Intuitively, larger PV plants exhibit a higher frequency of large fluctuations. All PV plants exhibited distributions with long tails – i.e. extreme events where the changes in power output are close to the size of the plant capacity do occur. For this study, this will be referred to as extreme ramp events. Events in the order of 50-100MW are of sufficient scale to potentially cause challenges for system operation in the NEM, although it should be noted that contingency reserves are generally set by the size of the largest dispatched generator or transmission network element, which are typically in the hundreds of MWs. The analysis also shows that the larger downward ramps occur more frequently that upward ramps, suggestive of the role of plant failures in these events. This analysis suggests that more regulation reserves may be required as utility-scale PV penetrations increase, in line with other literature exploring this question (Riesz *et al.*, 2011).

Table 3. Normalised frequency of occurrences of changes in PV power output at different magnitudes

	Change in output (MW) (number of events in 2016)						
	-105 to -45	**-45 to -10**	**-10 to -1**	**-1 to 1**	**1 to 10**	**10 to 45**	**45 to 105**
Royalla 20MW	N/A	0.0036% (91)	0.51%	99.02%	0.47%	0.0034% (87)	N/A
Broken Hill 53MW	0.000080% (3)	0.00064% (24)	0.76%	98.59%	0.64%	0.00061% (23)	0.000080% (3)
Moree 56MW	0.00021% (7)	0.0059%(198)	1.17%	97.78%	1.05%	0.0049% (165)	0.00% (0)
Nyngan 102MW	0.00023% (9)	0.035% (1,339)	2.53%	96.34%	1.07%	0.031% (1,209)	0.00010% (4)
All plants	0.00045% (18)	0.042% (1,702)	3.76%	93.13%	3.03%	0.040% (1,623)	0.00012% (5)

Figure 4 shows the cumulative frequency of the absolute changes in output at each PV plant, confirming that more than 85% of the time, the 4 seconds variability remains at zero. The impact of spatial smoothing across a large plant due to the fact that cloud boundaries do not affect the whole plant simultaneously can be observed from the graph. While 99.99% of the variability at Royalla (20MW) is less than 75% of the plant capacity, 99.99% of the variability at Nyngan (102MW) is within 30% of its plant capacity. This agrees with the results from other studies (Murata *et al.*, 2009; Marcos *et al.*, 2012; ARENA, 2015) on geographical smoothing of large-scale PV plants, which conclude that larger PV plants will not experience a sudden change in cloud cover simultaneously. The trend towards oversizing the DC side of PV plants will also act to reduce the effect of cloud transients, since the output will be capped at inverter capacity (e.g. peak output clipping in Figure 1 to Figure 3).

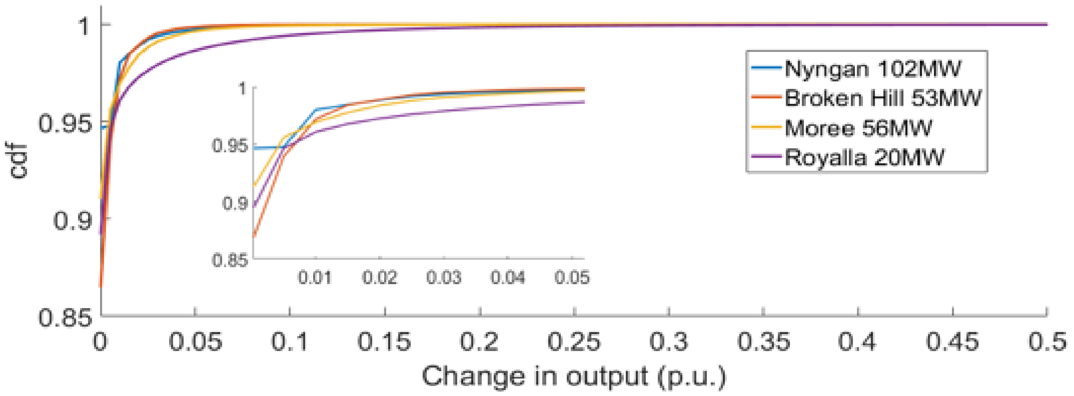

Figure 4. Cumulative probability of the change in power output at each PV plant

3.2. *Variability of combined PV plants*

Figure 5 shows the tails of the frequency distributions of variability for all four PV plants. When the outputs from all the PV plants are combined, there is a slightly higher frequency of large magnitude changes. This can be seen by the frequency distribution in Table 3, which shows a higher frequency of 4 second ramp events greater than 1MW than for individual PV plants. The combined output ("All plants") also results in one ramp event that is larger than any of the ramps of the individual plants. The combined changes in output also show that a few additional extreme ramp events have been created. Due to the limited current installed capacity of utility scale PV, this impact is as yet quite minor, however the results show more frequent occurrence of large magnitude aggregate changes in PV output with higher penetration utility scale PV. This result agrees with the trend summarised in Fattori and Anglani (2015). These results indicate that very short-term variability is likely to become more of a concern when the level of PV penetration is higher, regardless of the impact of spatial dispersion and uncorrelation of PV output over a long distance for short time periods.

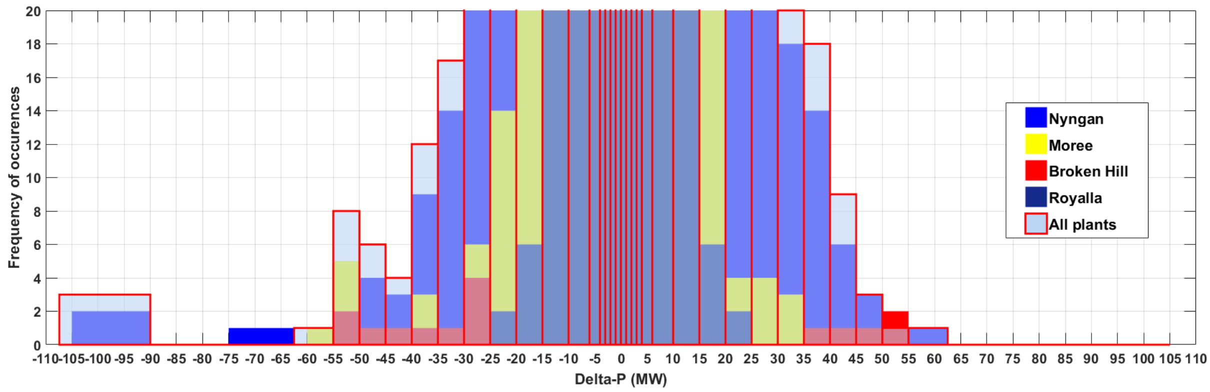

Figure 5. Tails of frequency distribution of variability in all four PV plants

4. Investigation of the extreme ramp events

In this section, extreme ramp events of the size greater than 100 MW that were observed in the variability analysis and which are particularly likely to be of interest to the system operator (Summers, 2017) are examined in more detail. The number of extreme ramp events are summarised in Table 4. The high number of events observed at Nyngan in 2015 is likely a result of the commissioning phase and a similar effect can be observed with the PV plant at Broken Hill. Observing the output of the plants on days with extreme ramp events show that it is unlikely for cloud transients to be the cause of these events, and that they are more likely the consequence of operational issues. Examples can be seen in Figure 6(a) and Figure 6(b), which show that Nyngan plant output tripping over 4 seconds on a day that appeared to be less cloudy. The investigation of extreme aggregate ramps created by combining all time synchronised PV plant outputs shows one trip with a magnitude of 107 MW (Figure 6(c)). This is equivalent to a small contingency event. If the difference between PV output and dispatch target was greater than 100 MW, it would constitute a small contingency event (Summers, 2017). Note that semi-schedule generators are not usually required to meet their dispatch target which are set by Australian Solar Energy Forecasting System (ASEFS) but may be constrained below the target. The dispatch target or forecasted value is calculated based on the actual MW output of the previous dispatch interval, in normal operation (i.e.no down-regulation order). If the MW output of the previous dispatch interval is down-regulated, the dispatch target is calculated from the available solar resource. The impact of another extreme ramp event with a size of 100 MW was investigated using frequency deviation (The nominal frequency is 50Hz) and no distinct correlation was found, as shown in Figure 6(d). This is likely to be because the dispatch target was already set at a low output, but may also be the results of automatic governor control of load and other generators.

Table 4. Summary of 4-second change in power output with the size larger than 50 MW

PV plant	Year	Number of events
Nyngan	2015 (Available from May)	28
	2016	6
Broken Hill	2015 (Available from August)	5
	2016	2
Moree	2016 (Available from February)	6
Combined output	2016	14

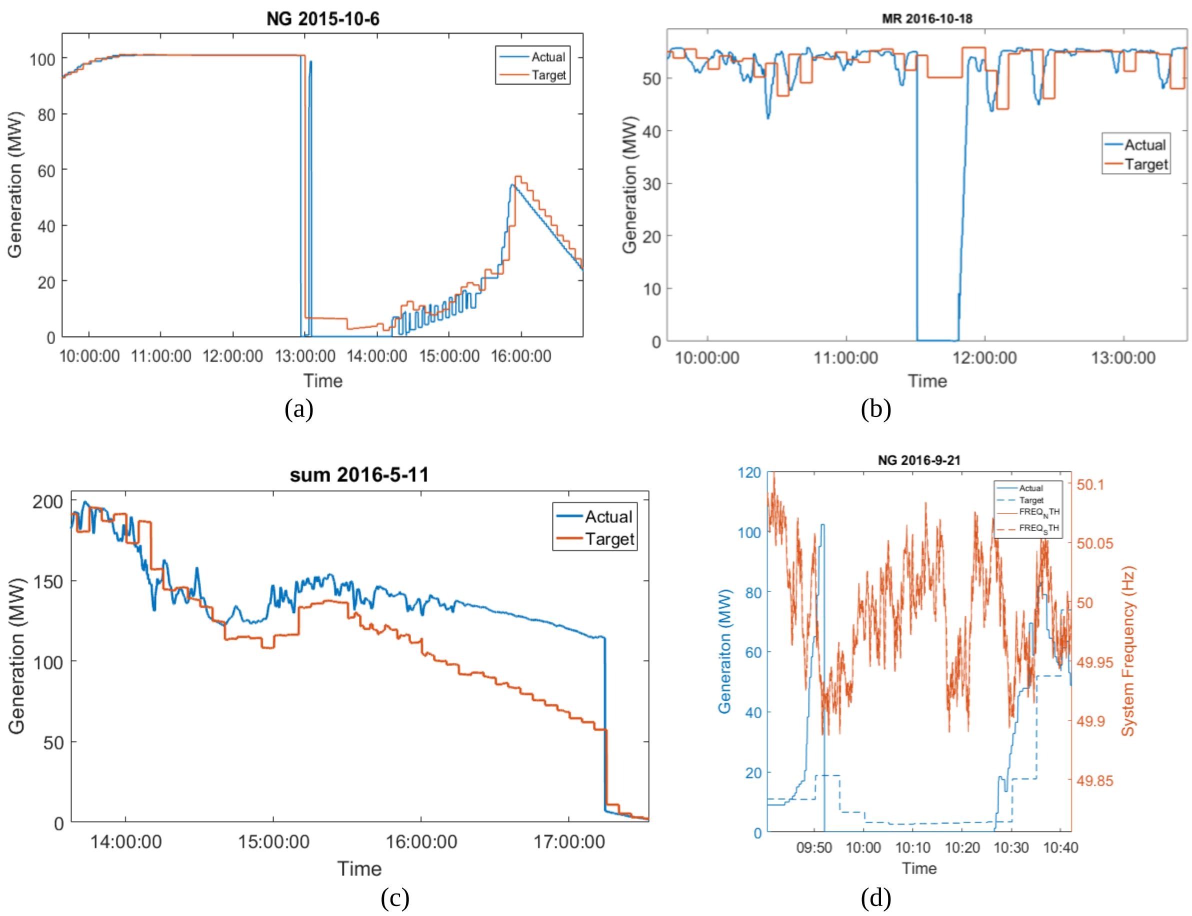

Figure 6. (a) The drop of 100% of power output at Nyngan; (b) The drop of 100% of power output at Moree; (c) the drop in combined power output from all PV plants of 107 MW; (d) the drop of 100% power output at Nyngan with time synchronised system frequency.

5. Conclusion

This study has analysed the short-term variability of the existing PV plants registered in the NEM. The analysis used 4-second data recorded by AEMO for FCAS causer pays calculations. The results of the variability study show that over 95% of the time, these very short-term output changes are within a 1 MW fluctuation and that the frequency of down-ramp events is slightly higher than up-ramp events. Although the effect of PV variability is limited by low PV penetration, the variability of the combined PV output shows an increasing frequency of higher magnitudes of variability. This suggests that at higher penetration levels, despite diversity smoothing effects, larger ramping events can be expected from the aggregate PV generation. An investigation into extreme ramp events revealed that these were likely not caused by cloud transients but rather operational issues.

Further studies should be conducted to deepen our understanding of this variability and its interaction with both utility PV plant dispatch targets and overall power system frequency management. This study has analysed historical data to assess the potential impacts of PV variability on system operation. Modelling of PV at higher penetrations will be necessary for a more comprehensive understanding of the impact of PV variability and uncertainty.

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