Propose a Comparison Method of the PV Variability based on Roof-top PV Solar Data of Australia

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Received: 21.07.2018 Accepted: 20.08.2018

Abstract- The use of renewable sources of energy is rising in Australia, and with solar energy becoming the most dominant; the solar (PV) roof-top plant penetration in the electrical energy distribution grid is increasing. As Australia is the sixth largest country in the world consisting of a diverse range of climates, this may be a concern to Distribution Service Operators (DSOs) as the variability in PV power output in different areas, climates/weather and even time of day. This means that DSOs are required to quantify these 'uncertainties' for different zones in Australia to aid in the energy planning. This paper will examine PV variability metrics to identify suitable PV variable metric based on purpose of application and propose a method to compare PV variability of large cities in Australia based on historical roof-top PV solar data. This proposed method examined variability metrics and find out suitable variability metric based on purpose of application. The comparative study shows that the PV variability and the amount of smoothing are not equal at all the distribution area in Australia and varies with geographical climatic scenario.

Keywords - PV Variability, Solar Power Prediction, smoothing, Storage, Grid fluctuation.

1. Introduction

Australia is divided into six states and two territories: South Australia, Victoria, Australian Capital Territory, New South Wales, Queensland, Western Australia, Northern Territory and Tasmania; with a majority of their respective population living in its capital [1]. Due to its geographical locations and size, Australia has a lot of climatic diversity which is divided into six climatic zones: temperate, grassland, desert, equatorial, subtropical and tropical zones. The temperate zone (New South Wales, Victoria, Australian Capital Territory, Tasmania), grassland (part of Queensland), and desert (South Australia) have four seasonal variations whereas equatorial (Major part of Northern Territory), subtropical (part of Queensland) and Tropical zones only have dry and wet seasons [1] [2].

Due to the continuous support of Federal and state government policy and schemes across Australia and immense social pressure, renewable energy systems (especially PV solar energy) are increasing dramatically and the installation and maintenance costs associated is decreased [3] [4]. Distributed roof top PV systems are a concern for DSOs because the PV varies in its output which creates uncertainty and makes it difficult to manage load and generation balancing; Market operators and system planners need to consider scheduling, dispatch generation, reserves and overall forecast about load and generation variability to create an efficient system. The Australian Energy Market Operator (AEMO) operates the National Electricity Market (NEM) through a gross pool market where electricity is traded non-stop. Dispatch bids occur every five minutes to maintain power quality, spot bids occur after every 30 minutes by averaging six dispatch bids. Several literatures [5, 6] made assessment and potential mapping of PV solar energy but did not consider PV variability. The author of [7] analysed the economic metrics in the levelized cost of electricity (LCOE) and the net present cost (NPC) with solar Global Horizontal Irradiance (GHI) data and discovered that the sensitivity to increase GHI is lower than the sensitivity to decrease GHI. The economic benefit can be achieved by dimensioning storage capacity based on solar variability and efficient tuning of solar tracking systems [8]. The authors of [9] also reviewed that PV solar energy cost depends on utilized solar irradiance. The AEMO also predicts the operating reserve by analysing generation variability and uncertainty. For this reason, it is crucial to analyse the PV variability and investigate the characteristics of the PV power output for different cities in Australia; this research that will benefit not only the researchers but power system planners and market operators [10] [11].

The authors of [12] investigated the PV variability of roof-top PV plants located at the same location (within 500m) and observed that the ramp rate and the power spectrum are nearly same. The authors of [13] studied the output of electrical power of 100 PV systems all over Germany in five minute intervals. This was done over a period of a year and using the frequency distribution of Ramps, they found that there have been no ramps more than 5% of installed capacity. The authors of [14] studied GHI data to observe the seasonal variations and smoothing effects of nine stations by analysing and aggregating three month's data in one minute interval. Through Fourier analysis they found that the frequency and magnitude of irradiance variability show smoothing effects of 20-50% variability and that clearer days show less variability[14]. The authors of [15] modelled aggregated empirical data to determine maximum fluctuations of 52 Japanese PV plants. For this model, the output fluctuation coefficient (ratio of maximum step change to standard deviation) is required as well as correlation coefficients between different regional PV plants. Standard deviation of a PV plant can be determined by using correlation coefficient and maximum step change can be determined by multiplying extrapolated standard deviation with output fluctuation data [15].

The U.S Department of Energy arranged one workshop regarding the subject of PV variability and PV penetration as a top concern of research in 2009 [16]. Similarly, the authors of [17] & [18] used Global Horizontal Irradiance (GHI) of the USA in different time scales with different plant scenarios of 100 MWp- one central power plant (100 MWp), 100 plants with 1 MWp, and 20,000 plants of 5 kWp each. In this study, researchers compared output variability of these three different scenarios, and the results showed that the relative output variability is 18%, 10%, and 1% respectively, which posits that small-scale, decentralized PV plants can reduce a significant amount of variability compared with others. The authors in [19] studied the PV electricity output data of 1 minute, 10 minute, and 60 minute interval. In this study, the output data of 67 PV plants from three different regions were examined by considering their step change metric above certain threshold capacities or threshold magnitudes. The findings are that the probability of step changes being more than 50% of the total capacity is 0.02%, and most of the power changes occur within 10% capacity. The authors of [20] studied the GHI Data of four PV plants in a year which ranged from 19 to 197 km, and aggregation of 4 PV plants reduces 40% ramp rate compared to a single PV plant.

Previous researchers analyse Global Horizontal Irradiance (GHI) data for PV variability analysis whilst assuming that the solar radiation is proportional to PV output power. These literature studies ignored the effects of PV panel efficiency, temperature, snow and soiling. To increase data efficiency, this study will consider the historical time series PV output power data collected from inverter nodes for PV variability analysis. Moreover, only a few research papers have examined suitable variability metrics for characterizing PV solar of Australia. This study will examine variability metrics by considering single and multiple PV roof top plants of different large cities in Australia and suggest a suitable method to compare PV variability.

In this study, the examination of the PV variability metric is provided in Section 2; the geographic smoothing of PV variability of different large cities in Australia are compared in Section 3; Section 4 proposes a method to compare PV variability and evaluate the method, and Section 5 includes the summary and future direction of this research work.

2. Examination of the PV Variability Metric

The most popular statistical approach of quantifying PV variability is either Ramp Rate (RR) or Power Spectral Density (PSD). Researchers consider either RR or PSD and this is where ambiguities arise. This study will examine these two PV variability metrics using time series PV output electrical data. The RR is calculated from step change PV output; the statistics and probability density (pdf) analysis of RR indicate variability of that PV plant. The width of pdf indicates variability where a wider pdf has a higher variability. The PV power fluctuation Ramp Rate (RR) is defined as:

Ramp Rates (RRs) :
$$\frac{P(t+\Delta t)-P(t)}{\Delta t} \quad \text{.....(1)}$$

Ramp Rates (RRs) (% of Installed capacity) :
$$\frac{1}{\Delta t}\times\frac{P(t+\Delta t)-P(t)}{Installed_{capacity}} \quad \text{...(2)}$$

The examination of these two variability metrics is investigated using time series power output (Watt) at the inverter node of a PV roof-top plant. The RR statistics analysis from a PV roof top plant located in NSW were performed and what was found was that the mean absolute value and the standard deviation of the RR is indicators for quantifying PV variability. The mean value of NSW PV Plant A is 42.95 [W min^{-1}] whilst the Std is [95.91 W min^{-1}].

The probability density (pdf) of RRs of the NSW PV Plant A is shown in Fig. 1.

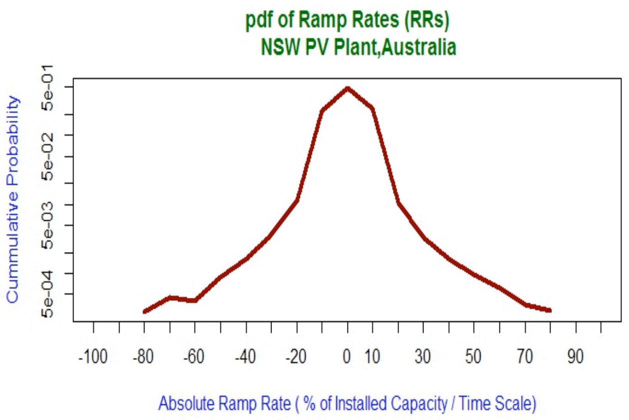

Fig. 1. Probability density function (pdf) of the ramp rate of NSW PV Plant A

The width of the pdf indicates PV variability. Wider pdf indicate a larger RR of the plant whereas narrow pdfs indicate smaller RRs. The RR analysis along with the cumulative probability density (cdf) indicate the threshold of the probability of RR occurrence (say P_{95}, P_{90}). The cdf of the NSW PV Plant A as shown in Fig. 2 shows that there is a 10% chance that the RRs will be larger than 8% of installed capacity (in magnitude 400 W min^{-1}).

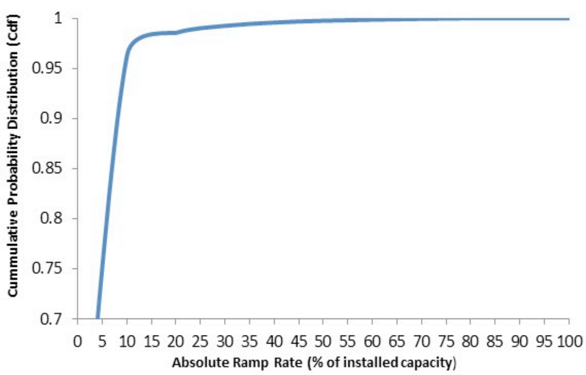

Fig. 2. Cumulative Probability Distribution of NSW PV Plant A in Australia with respect to absolute ramp rate (% of installed capacity).

Power Spectral Density (PSD) quantifies the PV variability in different scenarios (such as diurnal and seasonal) as variations in frequency. The low frequency oscillations indicate less variability whereas the high frequency oscillations indicate frequent fluctuations.

The power spectrum of the NSW PV Plant A is shown in Fig.3; from this the PV power output variation due to metrological events such as cloud movement over a range of frequencies can be analysed by PSD. The larger the PSD, the larger the variance in the PV power output; higher frequency oscillations indicates higher cloud movements whereas low frequency oscillations is observed due to daily and seasonal variations. The variability metric Ramp Rate (RR) and Power Spectral Density (PSD) are accepted by DSOs and the market planner for operating and planning purposes. The magnitude of the PV variability (RR) is important information for planning the storage capacity for balancing the grid; PSD, however, gives insight into the power fluctuation. Grid planners require faster ramping power sources to mitigate the higher fluctuation; lower frequency oscillations indicate the required amount of conventional power sources or base power sources. The PSD gives more information than RR but RR is an easier way to get planning information. Therefore, the usability of variability metric depends on DSOs and market planner's requirement.

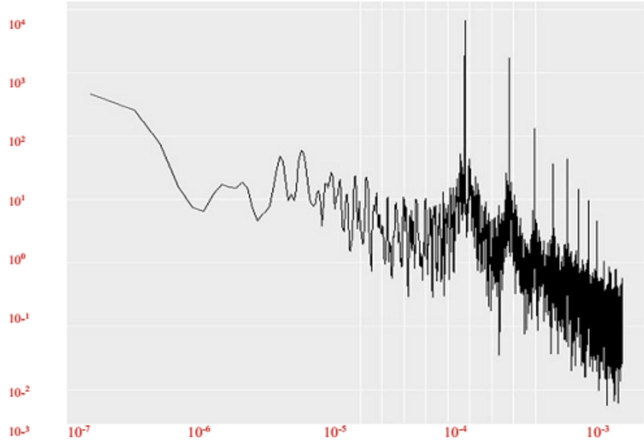

Fig. 3. Probability density function (pdf) of the ramp rate of NSW PV Plant A. The solid black line is PSD of NSW PV Plant A.

3. Geographic Smoothing of PV Solar in Australia

The aggregation of geographically distributed PV rooftop within a city can reduce PV fluctuation. In this study, geographically distributed PV roof top plants in different Australian cities will be analysed and will then discuss the amount of smoothing after aggregation compared to a single PV plant. The smoothing effect with regard to the number of PV roof top plants will be found by considering higher fluctuation duration.

3.1 Scenario 1: The Benefit of geographic smoothing in Victoria (Melbourne)

The benefit of smoothing after aggregation of all the PV Roof Plants are analysed in this section. The variability metric Ramp Rate (RR) of 20 plants (by considering mean output of 20 PV roof top plant's time series data) are compared to a single PV plant (VIC_SITE_V) in Victoria. These PV plants are selected from and around Melbourne city in Victoria. The output electricity data is measured in 5 minute intervals from October 2013 to August 2014. Fig. 4 shows PV roof top plants of Melbourne, Australia. The mean output power of twenty PV roof top plants from Victoria is compared to a single PV roof top plant's power output at the partly cloudy day (30th April,2104) shown in Fig. 5. Power output changes for every step change at the partly cloudy day shown in Fig. 6.

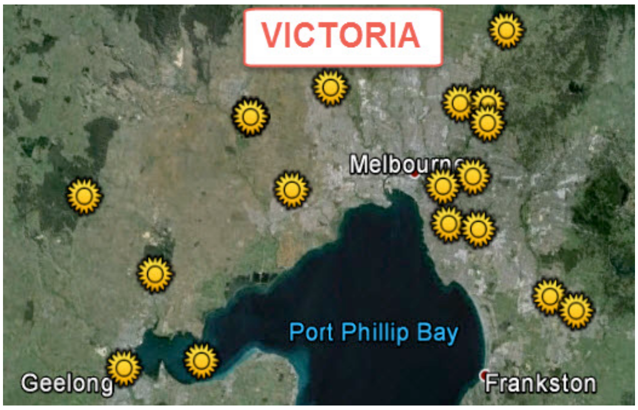

Fig. 4. PV roof top plant's locations in Victoria.

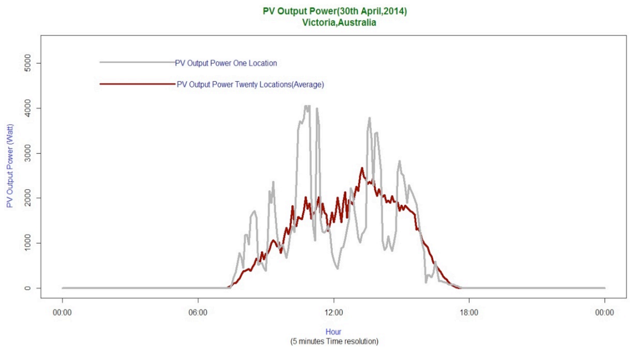

Fig. 5. PV roof top power output of 1 PV plants and Mean output of 20 PV plants at the partly cloudy day.

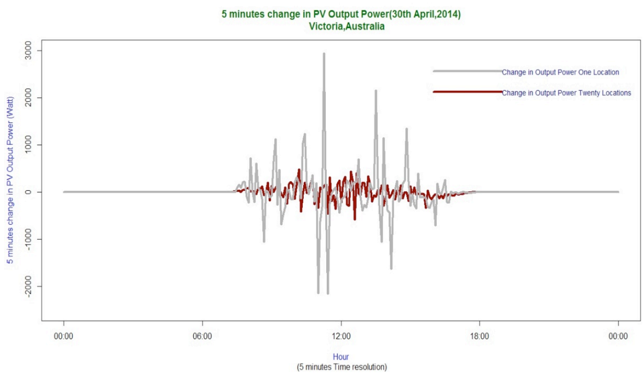

Fig. 6. Power output step changes of 1 PV plant and 20 PV plants at the partly cloudy day.

From Fig. 6, it is observed that the maximum power changes (ramps) of 1 PV plant is 2940 watt including several ramps larger than 700 watts but the mean output of twenty (20) plants show a maximum ramp of 578 watts with lower ramps at the partly cloudy day. This clearly shows that the mean output reduces PV output variability compared to a single PV plant. For more analysis, The Cumulative probability distribution (Cdf) of RR is shown in Fig. 7.

After aggregation, the variability of the 20 PV plants show that only 1.46% probability to exceed 10% of installed capacity whereas single plant's PV variability shows 15.27% of probability. There was a 95% probability of a PV variability of less than 5.8% of the installed capacity for the aggregation of 20 PV plants whereas the single PV roof top plant shows a 95% chance of a variability of 22.8% of the installed capacity. Fig. 8 shows the dependency of PV roof top plants and the benefit of aggregation to reduce PV variability.

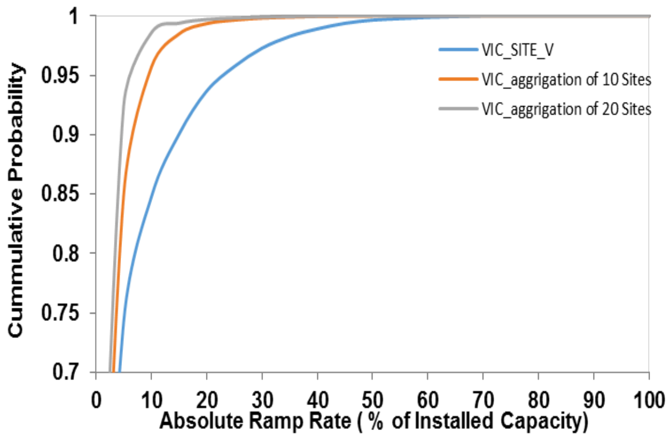

Fig. 7. Cumulative Probability Distribution of different scenario (1 PV plant, aggregated 10 PV plants, and aggregated 20 PV plants) with respect to absolute ramp rate (% of installed capacity), Melbourne, Victoria, Australia.

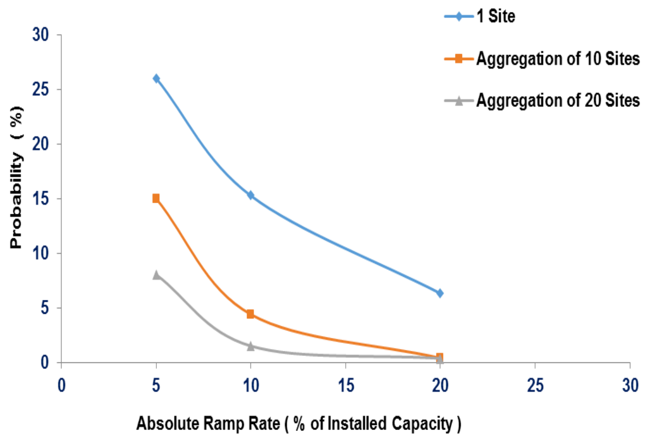

Fig. 8. Probability Distribution of different scenario (1 PV plant, aggregated 10 PV plants, and aggregated 20 PV plants) with respect to absolute ramp rate (% of installed capacity), Melbourne, Victoria, Australia.

From Fig. 8, it shows that the probability of PV variability of exceeding 5% of installed capacity is 26 % (1 PV plant), 15 %(10 PV plants) and 8% (20 PV plants). The probability of exceeding 10% of installed capacity is 15.27% (1 PV plant), 4.36% (10 PV plants) and 1.46 %(20 PV plants). The probability of PV variability of exceeding 20% of installed capacity is only 0.33% for both 10 PV plants and 20 PV plants whereas 6.36% for 1 PV plant. It is also observed that smoothing with 10 PV plants compared with a single PV plant is significant. For better smoothing distributed PV plants gives better result due to the nature of clouds. It can also be concluded that the large number of PV plants integrated into the Grid can reduce PV Ramp rates in Melbourne.

3.2 Scenario 2: The Benefit of geographic smoothing in Queensland (Brisbane)

The variability metric Ramp Rate (RRs) of 35 PV plants (by considering mean output power of 35 PV roof top plants) is analysed to study the benefit of geographic smoothing in Brisbane, Queensland. The electrical output data of 35 PV roof top plants is captured in 5 minute interval from October 2013 to August 2014. The geographical locations of PV roof top plants are shown in Fig. 9.

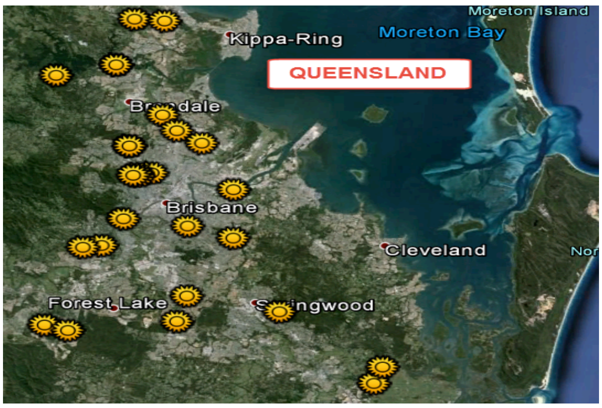

Fig. 9. Geographical locations of PV plants, Queensland.

Queensland is a state located in the north-eastern part of Australia. Brisbane is the capital city and it belongs to the sub-tropical climatic zone. The climate of Brisbane is characterised by two weather seasons: a hot and humid summer period with higher levels of rainfall and a winter period of comparatively warmer temperatures and less rainfall than Victoria. Fig. 10 shows the cumulative probability distribution (Cdf) with respect to absolute ramp rate (% of installed plant capacity) for four different scenarios (1 PV plant, Aggregation of 10 PV plants, 20 PV plants and 35 PV plants).

Fig. 10 shows that the probability of PV variability exceeding 10% of the installed capacity is 22.55% for 1 PV plant, 4.45% for 20 PV plants and 1.87% for 35 PV plants. The aggregation of 35 PV plants shows 95% probability of a PV variability of less than 6.1% of installed plant capacity whereas 49% of installed plant capacity for single PV plant. Aggregation of 20 PV plants shows 95% probability of the PV variability smaller than 9.8% of installed plant capacity. After the aggregation of 35 PV plants shows only 0.6% probability of the PV variability to exceed 20% of installed capacity and no ramps after 30% of installed plant capacity.

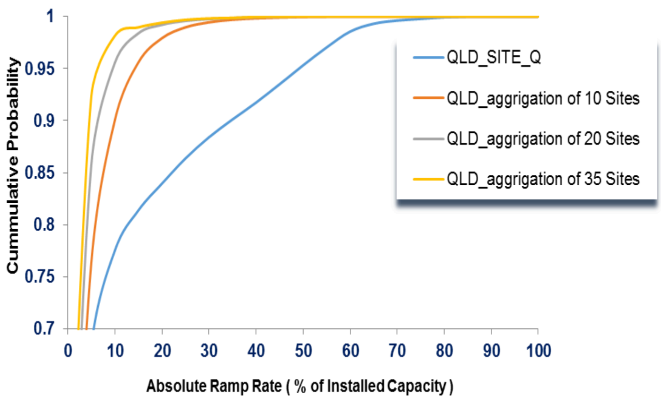

Fig. 10. Cumulative Probability Distribution of different scenario (1 PV plant, aggregated 10 PV plants, 20 PV plants and 35 PV plants) with respect to absolute ramp rate (% of installed capacity), Queensland, Australia.

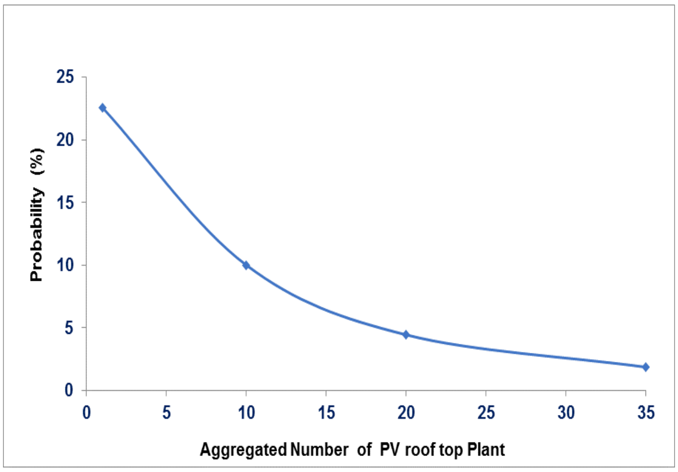

Fig. 11. Probability (%) to exceed 10% of installed plant capacity with respect to number of aggregated PV plants, Queensland, Australia.

From Fig. 10, it is observed that smoothing depends on the number of aggregated PV roof top plants in Queensland. Fig. 11 shows the probability of exceeding 10% of installed plant capacity with respect to aggregated number of PV plants. From Fig. 10 and Fig. 11, it can be concluded that smoothing depends on the number of aggregated PV roof top plants; a larger number of aggregated PV roof top plants will have less PV variability. From scenario 1 and 2, it is observed that aggregation of more PV roof top plants decrease PV variability. The PV variability metric RR analysis shows less PV fluctuation due to smoothing effect. Also, the cdf analysis is an easy way to examine impact of aggregation and the benefit of fewer fluctuations in the distribution grid.

4 Propose A Method To Compare PV Variability

The PV variability of different areas and the smoothing benefits of different cities are not the same; for balancing purposes energy market operators requires quantified PV variability data. The proposed method described below will compare the PV variability using both variability metric Ramp Rate (RR) and PSD analysis:

Stage 1: Select equally rated PV roof top plants around 1km of an area.

Stage 2: Maintain data uniformity. (Say, same interval and duration).

Stage 3: Investigate means, standard deviation of PV roof top plant's ramps of different cities in Australia.

Stage 4: Investigate the cdf of P95 of RR in different cities in Australia.

Stage 5: Investigate Power spectrum (PSD) of different cities in Australia.

Stage 6: Summarize the obtained results from stage 3, 4 & 5 to compare PV variability of different cities in Australia.

The proposed method will be evaluated in this study by considering PV roof top plants from four large cities in Australia, and the data is collected in 5 minute intervals, the duration is October 2013 to August 2014. PV roof top plants of Queensland is expressed as QLD_PV, and other plants of different cities are expressed as NSW_PV, VIC_PV, and SA_PV in this study. The mean and standard deviation value of Ramps of different cities are shown in Table 1.

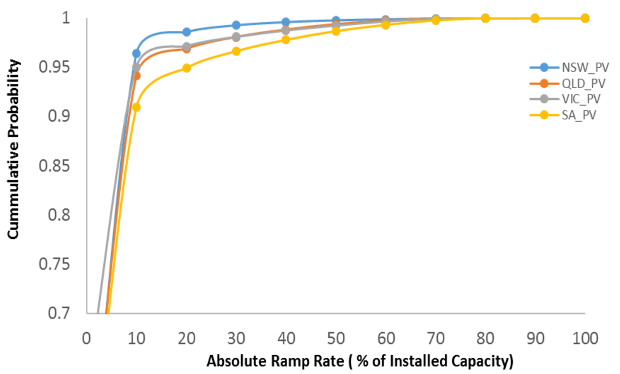

Fig.12. Cumulative Probability Distribution of different cities in Australia (NSW, VIC, QLD, SA) with respect to absolute ramp rate (% of installed capacity).

The cumulative probability distribution (cdf) of RR analysis is shown in Fig. 12 and the statistical analysis results are tabulated in Table 1. Figure 4.5 shows cumulative probability distribution of Ramps concerning ramp rate (%) of installed capacity of different cities of Australia. From Figure 4.5, it is observed that the NSW_PV located in Sydney has 3.64% probability of the PV variability exceeding 10% of installed capacity and only 0.756% probability of the PV variability exceeding 30% of installed capacity. Analysis of P95 means 5% probability of PV fluctuation larger than 9.8% of installed capacity. QLD_PV, located in Brisbane, shows 5.88% probability of the PV variability exceeding 10% of installed plant capacity and 1.95% probability of the PV variability exceeding 30% of installed capacity. There is only a 5% probability of the PV variability exceeding 10.5% of installed plant capacity. VIC_PV located in Melbourne shows 4.98% probability of the PV variability exceeding 10% of installed capacity of the plant and only 1.92% probability of the PV variability exceeding 30% of installed plant capacity. The statistical analysis P95 shows that there is only a 5% probability of the PV variability exceeding 10% of installed plant capacity. SA_PV located in Adelaide, South Australia shows 9.09% probability of exceeding 10% of installed capacity of the plant and 5.2% probability of exceeding 20% of installed capacity of the plant. The statistical analysis P95 shows that there is only a 5% probability of the PV variability exceeding 20% of installed plant capacity.

The power spectrum analysis helps to paint a clearer picture of the power fluctuation regarding frequency so that the power generated from PV roof top plants can be decomposed into continuous distinct frequencies over a period. The power spectrum of all the studied locations is calculated and shown in Fig. 5. In all the spectra, longer period cycle's fluctuation shows steady power spectral because of cyclic changes such as daily, seasonal variation, etc. Higher frequency fluctuations is affected by various metrological transformations such as cloud movement, furthermore, if there is an increase in power spectral density, there will be the decrease in frequency. The power spectral density is shown in Fig. 7. To enumerate this decrease in PV variability, the linear regression, with a period of less than 1 hour, is analysed. Linear regression is used to find the slopes within the period and the ratio of PSD values are tabulated in Table 1.

Table 1 shows the values of the different variability metrics. The absolute mean and standard deviation value (not absolute) of RR is a qualitative measurement of PV variability. The absolute mean value of RR magnitude of SA_PV shows 62.04 Wmin-1 whereas VIC_PV shows 38.37 Wmin-1. The standard deviation value of RR is nearly equal for NSW_PV and VIC_PV which shows 100 Wmin-1 whereas SA_PV shows the largest fluctuation 142.36 Wmin-1. The analysis of mean and standard deviation value indicates SA_PV has highest PV fluctuation and QLD_PV shows a higher PV fluctuation than NSW_PV and VIC_PV.

Table 1 shows the analysis of the cumulative probability distribution (cdf) of RR results of P_{90} and P_{95}. The P_{90} and P_{95} thresholds indicate that SA_PV shows the highest PV fluctuation as 20% of the installed plant capacity whereas the P_{90} and P_{95} threshold shows a PV variability of less than 10% of installed plant capacity of NSW_PV and VIC_PV. The statistical cdf analysis indicates that NSW_PV and VIC_PV show less PV variability than QLD_PV, and SA_PV shows the largest PV fluctuation among the four Australian cities.

The integral ratios of the power spectral density of less than one (01) hour period to the total period is shown in Table 1. The smaller ratio values of NSW_PV and VIC_PV indicate lower cloud movement whereas larger ratio values of SA_PV indicate larger fluctuation of PV variability and cloud movement. The results obtained from the proposed method show that the PV variability is higher in Brisbane; Queensland belongs to the subtropical climatic zone whereas Sydney and Melbourne belong in the temperate climatic zone. Clouds are roaming due to meteorological factors led by the climate. The highest PV fluctuation due to cloud movement is observed in Adelaide; South Australia belongs to Desert climatic zone.

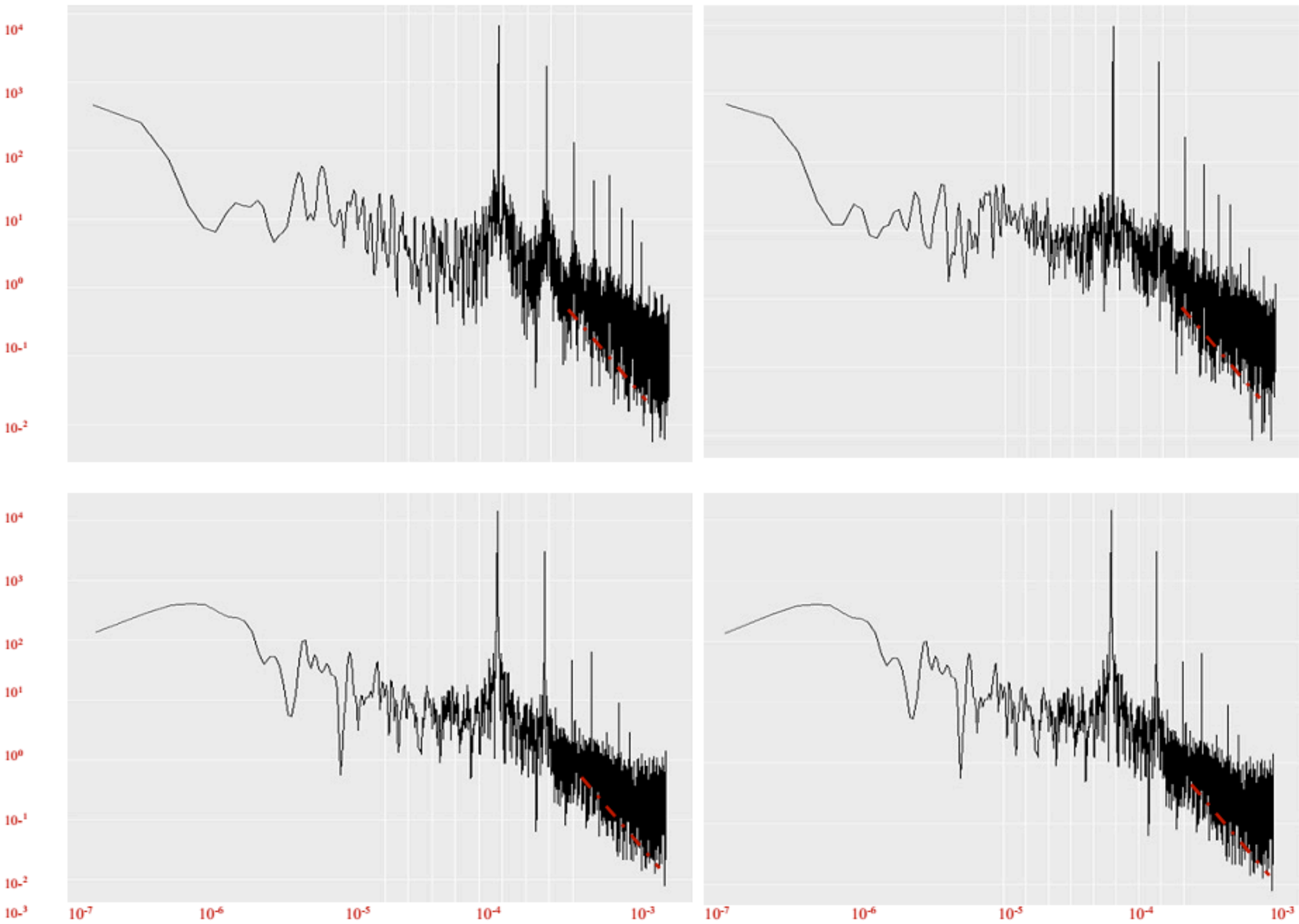

Fig. 13. Power spectral density of NSW_PV, VIC_PV, QLD_PV and SA_PV (from left to right). The solid black line shows PSD and the red line is the linear best fit line for time scale smaller than 1- hour.

Table 1. Comparison result of variability metrics

Geographical Location	Mean $\lvert RR \rvert$ [Watt min^{-1}]	Std (RR) [Watt min^{-1}]	P_{90}	P_{95}	$\frac{\int_{1hr} PSD}{\int_{all} PSD}$
NSW_PV	41.17	99.45	8.05%	9.8%	0.0282
QLD_PV	47.77	115.03	8.55%	10.5%	0.0286
VIC_PV	38.37	100.34	7.9%	10%	0.0293
SA_PV	62.04	142.36	9.6%	20%	0.0382

5. Conclusion

The PV variability of different cities (Sydney, Melbourne, Brisbane and Adelaide) in Australia (which belong to different climatic zones) is investigated in this paper. The PV plant NSW_PV and VIC_PV (temperate climatic zone), QLD_PV (subtropical climatic zone) and SA_PV (Desert climatic zone) are considered to analyse the impact of PV variability on the distribution grid. This study examines PV variability metrics and describes the suitability of each PV variability metric based on their role for DSOs. This study proposes a comparison method of PV variability of different cities in Australia. The analysis of PV variability using proposed method shows that the desert climatic zone has larger PV fluctuation compared to the subtropical and temperate zone as shown in Table 1. This study also shows that subtropical climatic zone tend to have more PV fluctuation than temperate climatic zone as indicated by its variability metrics. The research in this study will help Energy market operators to plan storage dimensioning, energy pricing and load management for different cities in Australia. Though the research work assumes Australian PV roof top data, the proposed method can be applied to other areas of the world, and a prediction model will need to be developed in further studies.

Acknowledgements

Special thanks to Overspeed GmbH & Co. KG, Oldenburg, Germany for making PV output data available to this study and for their Master thesis program. My sincere gratitude is dedicated to my supervisor Dr. Hans-Peter (Igor) Waldl for his critical and generous suggestions have given for my work. It is worth mentioning that his conceptual ideas and guidance at every stage have shaped my work to a perceptible direction.

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