Evaluation of the battery operation in ramp-rate control mode within a PV plant: A case study

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Abstract

Spatial and temporal variability of PV generation is a challenge for secure operation of the power systems. Several solutions are already proposed to deal with this issue. Among the proposed solutions, storage technologies (particularly battery) attracted more attention as a promising solution for the application in medium- and large-scale PV plants. While numerous research studies addressed optimal sizing and real-time operation of the storage systems in such applications, there is no study on the battery operation assessment in real-world application based on field data. In this paper, one year of experimental data from a 3.275 MWp PV plant with 600kW/760kWh Li-Polymer battery system is examined from different perspectives (e.g., battery energy, power, rate of change of power (RoCoP), and state-of-charge (SOC)) to draw insights from battery operation within the plant. The field data inherently contains system-wide losses, smoothing effect of the PV plant, and PV inverter operation for reactive power control, which provides a realistic as-

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sessment. Furthermore, several operational parameters (such as energy and power during ramp events) are evaluated and modelled using appropriate statistical tools based on experimental data. In addition, a simple supercapacitor sizing study is carried out to reveal the effectiveness of a hybrid energy solution for such applications. Observations and insights drawn from the proposed analyses will help future research on the battery sizing and operation to effectively account for real-world characteristics and requirements.
Keywords: Medium-scale PV and battery system, seasonality effect, smoothing, ramp-up and ramp-down, statistical modelling

1. Introduction

According to the Australian PV Institute (APVI) [1], installed PV capacity reached 5,855.6MW by January 2017 in Australia, which shows more than 61 times growth compared to January of 2010 (when total installed capacity was 95.7MW). While the number of small-scale PV installation is gradually dropping [1], the number of medium- and large-scale PV systems, i.e., 100kW~5MW and bigger than 5MW respectively, has been growing steadily in Australia in recent years. Only in 2016, 68 medium-scale and 12 large-scale solar projects with total capacity of 23MW and 319MW, respectively, were commissioned in the country [2]. While increasing PV generation can benefit the country in several ways, technical challenges regarding power system operation raised serious concerns, which have to be appropriately addressed [3, 4]. Among all detrimental impacts, variability of PV output power due to passing clouds (known as ramp-rate) is the one of paramount importance for frequency and voltage regulation of power system with high PV generation [5]. To reduce the negative impacts of the medium- and large-scale PV plants, electricity utilities imposed obligatory connection rules, such as ramp-rate and voltage violations limit, as a part of interconnection agreement [6, 7]. Any failure to meet the requirements could have financial consequences for the plant owners/operator.

To address the PV variability problem, researchers proposed various approaches and techniques to control rapid changes in PV production, as summarised in [8]. While distributing panels over a wide area can smooth ramp effects, it is not going to resolve the issue completely, as will be shown in this paper. Power-electronic-based control techniques are also developed in literature to smooth PV output fluctuations within short-time intervals [9, 10]. These approaches, however, cannot compensate ramp events with high energy and power due to technical limitations of power electronic interfaces. Most recent solutions are mainly focused on the application of various storage technologies (specifically battery) for medium- and large-scale PV ramp compensation. Optimal and intelligent algorithms are proposed in [11, 12, 13, 14, 15, 16, 17, 18] to operate battery in ramp-rate control mode . Also, storage sizing for PV ramp-rate control has been reported in multiple papers, e.g., in [19, 20]. In these studies, the mathematical model of a single PV module is used to generate PV power time series to further calculate ramp-rates in different time resolution. In addition, pure simulation studies were mainly employed to assess battery operation under the ramp-rate regulation mode. To the best of our knowledge, however, there is no research study that looked into battery operation in ramp-rate control mode using field data.

In this paper, operational data from a 3.275 MWp PV plant with 600kW/760kWh Li-Polymer battery system is utilised for analyses from different perspectives. The PV plant is located at the University of Queensland (UQ) Gatton campus, Australia. The plant with battery system is in operation for more than a year and a half. The battery system is operated by a central supervisory controller in different modes based on pre-defined rules. One of the battery operation modes, which is considered in this study, is designed to compensate quick drop in the PV output in real-time. Despite other research studies, where mathematical models and simulation framework were used to identify ramp requirements, actual ramp incidents from the PV modules and battery response to the events are investigated in this study. Therefore, real-world operational characteristics of the plant, such as system-wide losses, inverter's operation for smoothing PV output and reactive power control, PV module degradation, etc., are represented in the experimental data and consequently in the analyses. To shed light on the battery operation in the ramp-rate control mode, this paper offers a thorough evaluation of battery operational behaviour in terms of energy, power, rate of change of power (RoCoP), and battery state-of-charge (SOC). Additionally, time gap between consecutive ramp events, which have been compensated by the battery, are analysed to identify technical requirements in real-world operational conditions. Seasonality effect on the ramping events is also investigated and statistical behaviour of the battery operation is derived from the experimental data. The key findings of the analyses can be used in the future battery sizing and operation studies to account for stochastic nature of the underlying system. To show the effectiveness of the hybrid energy storage system in ramp-rate control mode, a simple super-capacitor sizing study carried out. It is shown that low-energy incidents (which often coincide with low-power events) can be conveniently mitigated by super-capacitor. This will, in turn, help to extend battery lifetime and improve economic operation of the whole plant. Ultimately, ramping incidents on the DC and AC sides of the PV inverters are assessed for a year of field data. As a result, a set of new requirements are identified, which will have implications on the future research in this area.

The rest of the paper is organised as follows. Section 2 explains system under study including the plant control mechanism and interconnection agreement with the local utility. In Section 3, a general overview of the battery operation under ramp-rate control is presented. Moreover, statistical tools and concepts, which have been used for the analyses, are outlined and explained in this section. Battery operation is then evaluated from different perspective in Section 4. Finally, paper is concluded in Section 5.

2. System Under Study

The UQ owns and operates a 3.275 MWp PV plant along with 600kW/760kWh battery system at the Gatton campus, located in the Lockyer Valley region of South East Queensland, Australia. A schematic diagram of the plant is shown in Fig. 1, in connection to the UQ Gatton substation and local utility grid. The UQ Gatton 11-kV substation has two complementary parts. Onsite diesel generator (1MVA), capacitor banks (2×550 kVAr), and most of campus loads are connected to the left busbar. Power can flow between the two busbars through a normally closed circuit breaker, as shown in Fig. 1. The campus load is served by onsite PV generation and storage as well as utility grid. Excess PV generation, when available, is exported to the grid using the same circuit. As it is shown in Fig. 1, there are five PV arrays, three of them are fixed-tilt (FT) arrays (684KWp DC each), one array with single-axis (SA) tracking system (684KWp DC), and the fifth array with dual-axis (DA) tracking mechanism (684KWp DC). Each array is linked to the substation through an exclusive inverter, which is limited to deliver 630 kW AC at any moment of time. Interested readers are referred to [21] for more detail on the plant operation.

Li-Polymer batteries are installed in the plant. As shown in Fig. 1, battery power/energy capacity is divided into two 300kW/380kWh banks, each of which is connected to a 300kVA, 415V, 3-phase inverter capable of sourcing/sinking reactive power at ±0.9 power factor. The two inverters are connected to the campus substation through a single 1000kVA transformer. Each battery bank consists of four racks in parallel, as shown in Fig. 1, where 10 battery modules are assembled in series in every rack. Every module contains two parallel strings, where each string has 18 battery cells in series. Voltage at the DC side of the battery inverter varies between 576 and 748 V based on the battery SOC and internal resistances. As expected, several constraints are defined for battery operation in the central supervisory system (CSS). For instance, battery SOC is strictly limited between 15% and 95%. The CSS operates the whole plant consisting of PV arrays, battery storage system, diesel generator, capacitor banks, and local grid connection. A comprehensive SCADA system is implemented to measure, collect, and communicate data within the plant, which is essential for the CSS operation. More details about smart metering and data collection in the plant can be found in [21].

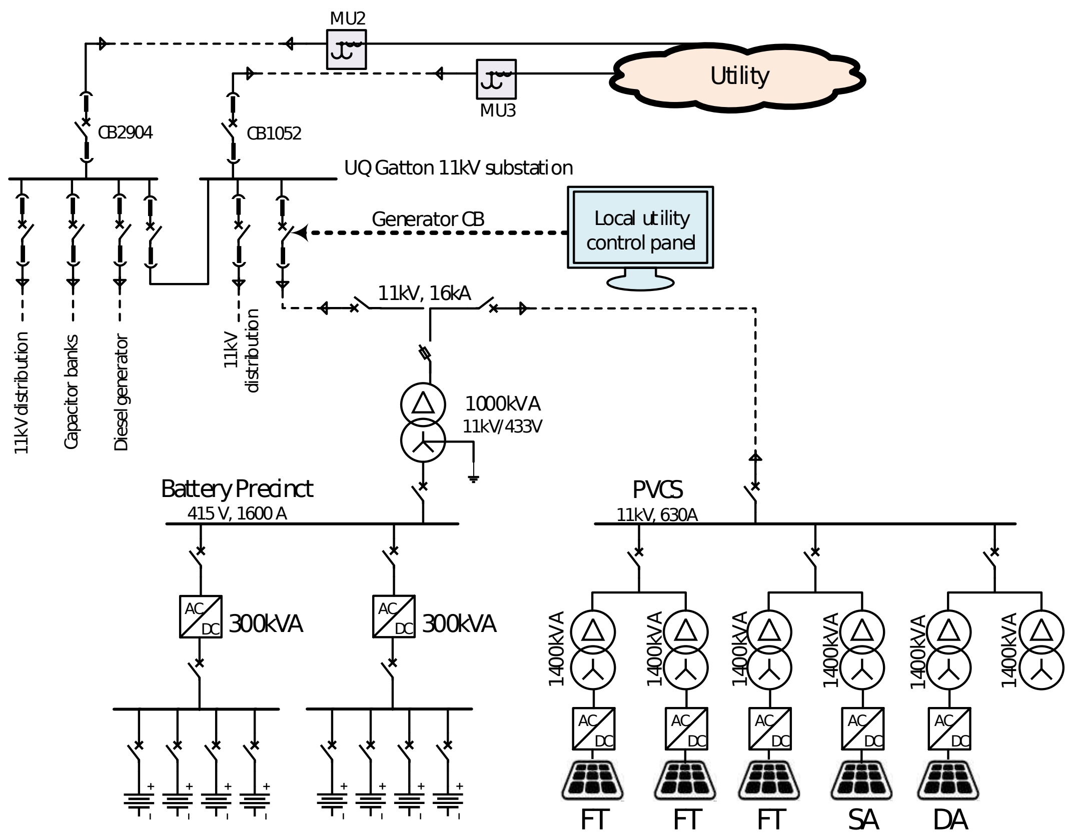


Figure 1: Single-line diagram of the Gatton PV plant and local network interconnection

2.1. Agreement with the Local Utility

According to the agreement, PV inverters are limited to export 630 kW AC. Additionally, they are required to regulate reactive power such that at 30% or more of the rated inverter output, the amount of reactive power is at least 0.395 times the active power output [21]. This way, “Ramp Mode” is defined for the PV inverters to regulate ramp-up events [21]. There are multiple agreement on the voltage level and violations, which are not related to battery operation, and not discussed in this paper.

2.2. Battery Control Mechanism

Battery, similar to other devices in the plant, is monitored and controlled by the CSS directly. In particular, ten operation modes (rules) are defined for the battery with predefined priorities. `Delta Solar`, as one of the operation rules, is activated when solar power reduction exceeds a certain level. Battery contribution to the compensation of ramp-down events decreases slowly when solar power generation stables at a certain level. This summarises ramp-down control mechanism provided by the battery. In `Solar Charge` mode, on the other hand, battery is charged when PV generation exceeds 800kW during certain hours of each day. This is not exactly ramp-up control as it operates based on the magnitude of the PV generation rather than the change in the PV output. Other battery modes are not related to either ramp-up or ramp-down events. Besides battery system, as explained in subsection 2.1, PV inverters are setup to limit extreme ramp-up events. Therefore, battery does not contribute in regulating ramp-up incidents in the Gatton plant. As a result, battery performance will only be studied during ramp-down events in this study.

3. Overview of the Battery Operation and Analysis

In this section, a general overview of the battery operation during ramp-down events is given for one year of field data. Then, statistical terms and methods, which have been used in Section 4, are explained.

3.1. General Overview of the Ramp-Down Control Mode

As it was explained in subsection 2.2, `Delta Solar` mode is activated during ramp-down events of 10kW/s or higher. While the CSS regulates plant operation in second-by-second basis, our analyses are carried out for minute-by-minute data for practical reasons (such as memory management and tractable computational requirements). Data are averaged every minute and relevant parameters are converted, when needed. For instance, ramp-down event is re-defined as 600kW/min (instead of 10kW/s) or larger reduction of the PV generation. One year of the battery operation data starting from 1$^{\text{st}}$ of March 2016 is utilised for analysis. For simplicity, data for one battery bank is assessed because the two banks show almost identical behaviour throughout the year.

In total, battery was discharged in `Delta Solar` mode for 7,928 minutes (equivalent of 11 days, 19 hours, and 46 minutes accumulatively) throughout the year. Total energy discharged from the battery during this time was about 12.9 MWh per bank. This equals to 21.3 full cycles (based on the installed capacity of the battery bank and 80% rated Depth-of-Discharge (DoD)) cumulatively during discharging mode, calculated as follows:

$$\text{Cycles} = (2 \times DoD \times E_{rated})^{-1} \times \sum_{i=1}^{7928} |P_i| \times \frac{1}{60} \quad (1)$$

where P_i is the discharge power in i$^{\text{th}}$ time instance in kW for battery bank 1; DoD is the rated DoD of the battery (0.8 p.u.); and E_{rated} is the rated capacity of the battery bank 1 in kWh (380 kWh). From the annual operation point of view, 21 cycles per year is insignificant, which justifies stacked application of the battery in such systems. From the battery operation standpoint, however, this means that the battery undergone almost 1.8 cycles per day in `Delta Solar` mode, i.e., 21.3 cycles in almost 12 days. This is relatively intense as the battery at the UQ Gatton plant experiences about half a cycle on average per day. It further shows that battery capable of deep cycling with high power, such as Li-based technologies, are needed for the PV ramp-rate control application. In Section 4, significance of different parameters on battery operation during `Delta Solar` mode will be investigated thoroughly.

3.2. Analysis Methods and Definitions

In this paper, different statistical tools and concepts are used to perform the analyses. While average and standard deviation (SD) are calculated for the experimental data to compare performance and operational stress on the battery in different circumstances, Skewness and Kurtosis are computed to characterise the stochastic nature of the data and detect potential outliers. More specifically, skewness is used as a measure of asymmetry of any density and probability distribution of a random variable about its mean [22]. The skewness value can be positive or negative, or undefined. For a unimodal distribution (i.e., a distribution with only one clear-cut peak), negative skew indicates that the tail on the left side of the probability density function is longer or fatter than the right side. Non-zero skewness means that the random variable is not following a normal distribution [22]. Therefore, it would be a mistake to statistically model such random variables with normal distribution. Kurtosis is a descriptor of the shape of a distribution. Higher kurtosis is a sign of rare extreme deviations (or outliers), as opposed to frequent reasonably-sized deviations [22]. The sample kurtosis is a useful measure of whether there is a problem with outliers in a data set. Larger kurtosis indicates existence of a serious outlier, which is recommended to be removed from dataset.

Modelling statistical behaviour of random parameters are very useful in sizing studies and developing operational algorithms for battery. These models can be applied to account for stochastic nature of the battery operation in such studies. Since ramp events are random in nature, they can be modelled by finding appropriate density or probability distribution for given experimental data. To find the best distribution (either frequency or probability) for a given set of data, a measure of comparison is needed. In this paper, corrected Akaike Information Criterion (AICc) [22] is used which is corrected AIC for sample size, i.e., it is independent of the sample size. It is an information-based criteria that assess model fit based on -2Log-Likelihood [22]. While AICc can help to find the best distribution for a set of data, it is not able to determine the accuracy of the fitted distribution. Therefore, quantile-quantile plot (Q-Q Plot) is used to visually verify the validity of the best fit on the experimental data [23]. In a Q-Q plot, theoretical expected values will be computed based on the fitted distribution function on x-axis and the results are compared with the experimental values on Y axis. If the experimental data truly follow the distribution, points on the Q-Q plot will follow a straight line.

Frequency histograms are also used to draw insights from experimental data. Selecting appropriate number of bins in a histogram, which further defines the width of the bins, is critical for data with outliers. In this study, number of bins in a histogram is selected based on Freedman-Diaconis rule [24], which is less sensitive to outliers in the data and more suitable for heavy-tailed distributions. The optimal bin-width is calculated by:

$$h = 2 \times IRQ \times n^{-1/3} \tag{2}$$

where IRQ is the interquartile range of data; and n is the number of samples. Then, optimal number of bins is:

$$N = (max^{\text{data}} - min^{\text{data}})/h \tag{3}$$

The tools and concepts, explained in this subsection, are used in the next section to evaluate battery operation and performance in ramp-rate control mode. The analyses will lead to identify useful insights for the battery sizing and operation studies during ramp-down control within a medium-scale PV plant.

4. Battery Operation Analysis

In this section, battery operation is evaluated from different perspectives using available data through various statistical methods. Please note that all the analyses in this section have been done for one battery bank. Similar observations can be extended to the second battery bank. Different parameters are calculated based on the raw data, which are shown for a hypothetical ramp-down event in Fig. 2. ∂P_t is the ramp value in kW/min: and RoCoP_t is the RoCoP at time t. The concept of "unique ramp-down event", "energy of the incident", "maximum power of the incident", "SOC at the end of the incident", and "time gap" between consecutive events are illustratively shown in the figure.

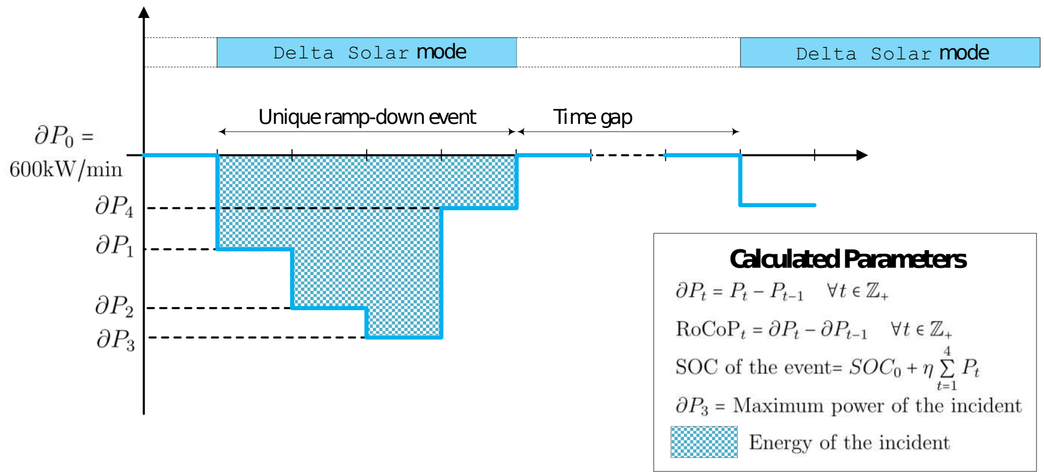


Figure 2: Calculated parameters from raw data for the analyses

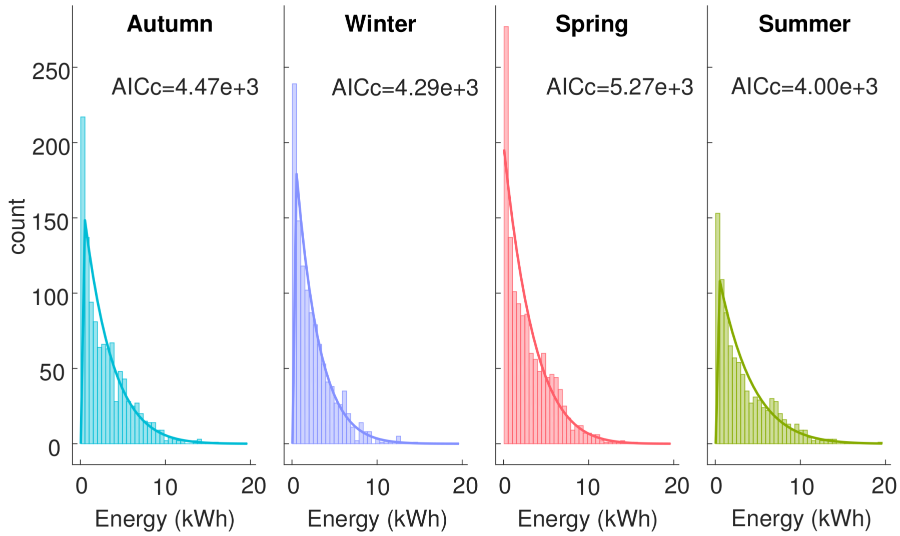
4.1. Energy

The amount of energy extracted from the battery during ramp-down events is of paramount importance because it affects battery health and its readiness for the future incidents. It is also one of the two critical factors (the other one is ramp-down power) in battery sizing studies in literature, e.g., [20, 25]. The general statistics for every unique ramp-down event are reported in Table 1 for different seasons and annual values. A "unique ramp-down event" is defined as a sequence of battery discharge with possibly different level of power without interruption during the `Delta Solar` mode. Based on the raw data, the maximum annual energy drained from the battery occurred in spring, where battery was discharged for 41 minutes consecutively to compensate quick drop in the PV generation. This incident drained 163.1 kWh from the battery. It is clear from Table 1 that this event is far bigger than the next maximum value in the whole dataset as well as within the samples of spring. Also, the large Skewness and Kurtosis values in spring, compared to other seasons, further proves that the event is an outlier in a statistical sense. It means that although the incident actually took place in spring, it does not represent typical behaviour of the parameter, as it only occurs once in a lifetime. In the battery sizing studies, such an event is a rare incident, where accrued penalty does not justify the cost of an over-sized battery. Therefore, the incident can be treated as an outlier to be safely removed from the dataset for the rest of the paper. Maximum, average, SD, Skewness, and Kurtosis of the samples in spring without outlier are given in parenthesis in Table 1. It can be seen that the new parameters in spring are reasonably close to the values of other seasons. Also, Kurtosis is significantly decreased, which follows the general perception of Kurtosis as being highly affected by the outliers in data.

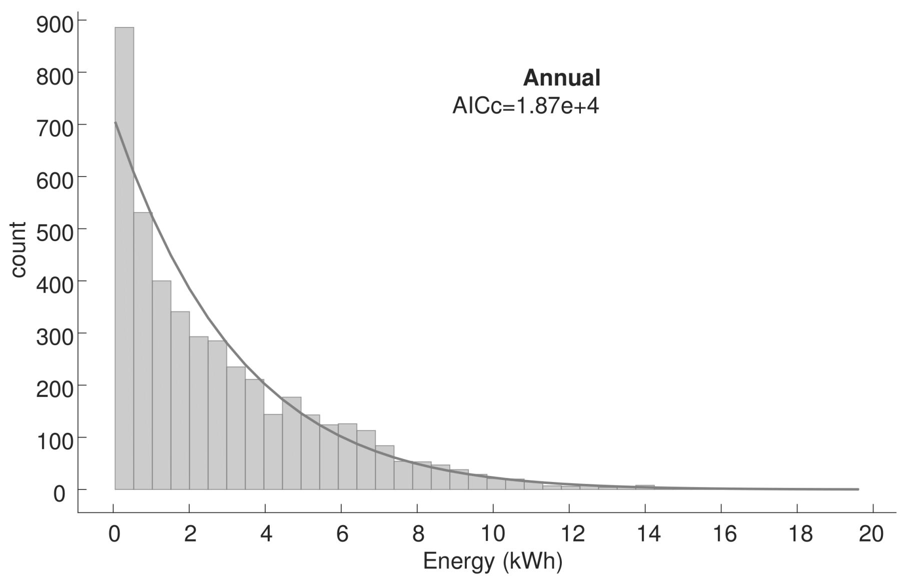
Table 1: General statistics for Energy samples (in kWh) during `Delta Solar` mode.

Season	Maximum	Minimum	Average	SD (σ)	Skewness	Kurtosis
Autumn	16.1	0.053	2.9	2.7	1.31	4.83
Winter	14.7	0.051	2.5	2.3	1.46	5.48
Spring	**163.1** (15.3)	0.05	**3.05** (2.92)	**5.21** (2.68)	**22.70** (1.13)	**693.499** (4.04)
Summer	19.6	0.052	3.4	3.13	1.22	4.25
Annual	**163.1** (19.6)	0.05	2.9	**3.63** (2.71)	**20.02** (1.32)	**861.63** (4.79)

According to Table. 1, maximum discharging event in terms of energy occurred in summer, where the average and SD values are the highest. Among all seasons, winter shows the most random behaviour because of the highest Kurtosis. The average value is the lowest in winter and autumn, which is not surprising as the sunlight intensity is less in these seasons. From energy perspective, a battery bank of 21.7 kWh capacity (considering 90% round-



(a) Seasonsal



(b) Annual

Figure 3: Histogram of energy samples without outlier

trip efficiency for the battery) would be sufficient to successfully compensate ramp-down events. In other words, this observation defines an upper limit the kWh capacity of the battery in a sizing study, which statistically would be able to compensate all ramp-down incidents. Based on this observation, it can be concluded that an appropriate operational algorithm should preserve at least 21.7 kWh energy in the battery at all times to effectively ride through ramp-down events, when they occur.

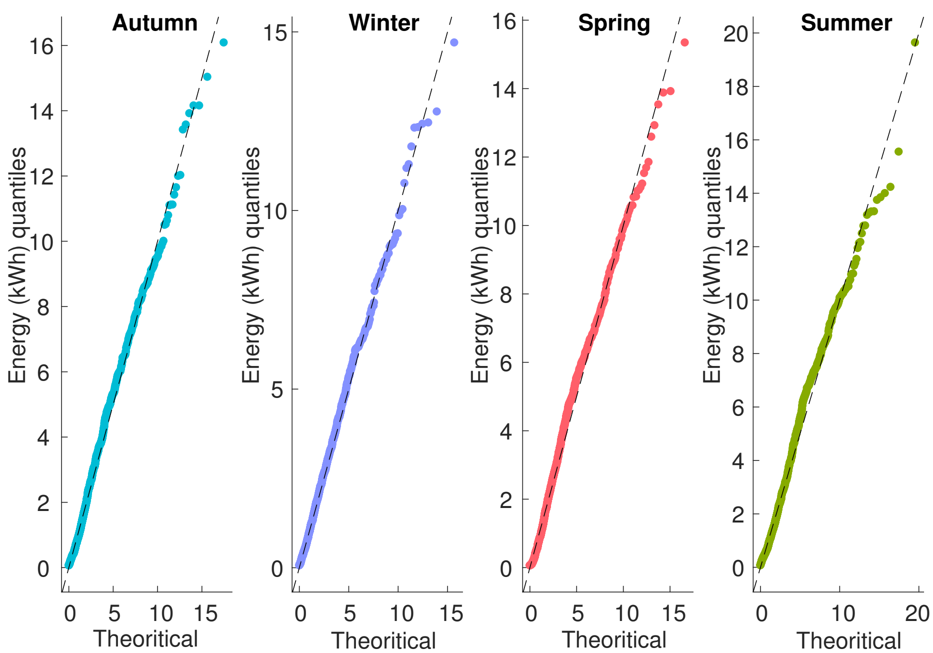


Figure 4: Q-Q plot for energy samples based on "Generalised Pareto" DF

Additionally, it can be inferred from non-zero skewness in all seasons that statistical behaviour of the samples is not following a normal distribution closely. While considering only ramp-down events might seem to cause the non-normal behaviour, it will be shown in Subsection 4.5 that it is true when both ramp-up and ramp-down events are considered. This further has been verified by fitting the best density function (DF) on the experimental data, as shown in Fig. 3. It contradicts with many papers in this area, which assumed normal distribution of ramp events in their analysis [13, 14].

Seasonal and annual histogram of the battery energy, without outlier, are shown in Fig. 3a and 3b, respectively, along with the best DFs. In all cases, "Generalized Pareto" found to yield the best fit on the experimental samples. To further show that the samples are not following a normal distribution, seasonal Q-Q plot is shown in Fig. 4 for "Generalised Pareto" DF. It can be seen that the field data is following the DF very well. The larger values seem to deviate from the DF, which shows a longer tail in the distribution. The AICc values of the fitted DFs are printed on the figure. One important observation from the AICc values is that partitioning experimental data into different seasons yields better statistical models.

According to Fig. 3, there are many discharging instances with very low energy (as low as 0.05 kWh). Small discharge events can adversely influence battery lifetime due to memory effect, as described in [26]. Using super-capacitor alongside battery can mitigate these events properly. According to [27], super-capacitor size in a hybrid storage system can be calculated by:

$$C_{sc} = \frac{4\,max(|E_{sc}|)}{v_{sc,max}^2 - v_{sc,min}^2} \tag{4}$$

where E_{sc} is the maximum energy in Joules; $v_{sc,max}$ and $v_{sc,min}$ are the maximum and minimum operational voltages of the super-capacitor; and C_{sc} is the capacity in Farads. Since the battery's inverter operates within 576~748 V range on the DC side, the same operational voltages are assumed for super-capacitor, i.e., $v_{sc,max} = 748$ and $v_{sc,min} = 576$. Considering that voltage of a super-capacitor's cell is typically between 2.3 to 2.75 Vdc [28], 272 cells are needed in series to raise the voltage to the desired level. If it is intended to cover 50$^{\text{th}}$ percentile of ramp-down energy by super-capacitor (i.e., 2.1 kWh which is about 7.56 MJ), then a 33.2 F super-capacitor is required. This is the amount of energy which super-capacitor should deliver during several minutes. However, energy delivery duration in capacitors depends on the capacity and equivalent series resistance (ESR), R_{ESR}, of the capacitor (excluding external resistances):

$$\tau = R_{ESR}.C_{SC} \tag{5}$$

where 1τ is the time that takes a capacitor to discharge to 36.8% of its final voltage. Since it is assumed that the super-capacitor can only be discharged up to 50% of its final voltage, according to [27]:

$$C_{sc} = \frac{36.8}{50}.\frac{\tau}{R_{ESR,cell} \times N_s} \tag{6}$$

where τ = 60 seconds for 50$^{\text{th}}$ percentile of the unique events' duration; $R_{ESR,cell}$ is about 1 $m\Omega$ per cell for modern super-capacitors; and N_s is the number of cells in series (272 in this study). By doing the calculation, battery capacity should be at least 162.3 F. In Section 4.2, the required power will also be determined.

If super-capacitor was used for the one year of the experimental data at hand, 1.86 MWh of energy throughput (about 14.5% of total energy delivered by the battery) could have been provided by the super-capacitor. It also could have released the battery from operating in `Delta Solar` mode for 2,235 minutes (worth of 1 day, 13 hours, and 15 minutes) to operate in other modes to provide other services to the plant. Moreover, it could have extended the battery lifetime by avoiding partial discharges and reducing accumulated energy throughput.

4.2. Power

Besides the energy extracted from the battery, the charge/discharge power magnitude is an important factor on the battery degradation. It also plays an inevitable part in any sizing and operation study [20, 25]. Therefore, discharge power magnitude, averaged per minute, is considered for investigation in this subsection. General statistics of the battery power in `Delta Solar` mode are derived for annual data as well as different seasons, reported in Table 2. Seasonal and annual frequency histograms of the samples are also shown in Fig. 5a and 5b, respectively. Important remarks from the figures and the table are summarised below:

Table 2: General statistics of power samples (in kW) during `Delta Solar` mode.

Season	Maximum	Average	SD (σ)	Skewness	Kurtosis
Autumn	301.9	95.0	70.6	0.66	2.53
Winter	312.0	87.0	67.8	0.85	2.94
Spring	325.4	101.8	80.1	0.66	2.39
Summer	331.2	110.1	80.6	0.62	2.37
Annual	331.2	98.2	75.4	0.72	2.59

• Similar to the energy samples, the experimental power samples are best modelled using "Generalised Pareto". The largest incident occurred in summer, similar to the energy values, where power magnitude was 331.2 kW. Summer also experiences higher ramp-down power on average whereas winter has the lowest average value. Winter, however, represents more stochastic behaviour compared to the other seasons because of higher Skewness and Kurtosis. These observations are aligned with those inferred from the energy samples in the previous subsection.

• DFs fitted on the seasonal data are more accurate compared to those ones fitted on the annual samples based on the AICs values given in Fig. 5. As shown in the analyses so far, partitioning data into different clusters (e.g., seasons) have a considerable impact on the accuracy of the statistical models. So far, it is shown that seasonality pattern exists in the battery operational data. However, it is worth to use clustering techniques to identify different categories in data beyond seasonality, and to fit more appropriate DF on every cluster. This way, more accurate models can be developed from the experimental data, which will be useful in the battery sizing and operation studies in the future.

• In general, it is more difficult to statistically model the battery power during ramp-down events compared to the energy samples. This further means that a larger error should be anticipated for power in sizing or operation studies, e.g., when predicting power for real-time operation.

• 86$^{\text{th}}$ percentile has power equal or less than 150 kW, which is half of the battery rated capacity. This is good for battery health since high-power incidents have occurred less frequently over the year.

In Fig. 6, the maximum power of every unique event is plotted against the accumulated energy of the same event. It can be seen that there is almost a linear relationship between the two parameters. Essentially, the high-power incidents coincide with the high-energy events. The correlation coefficients for seasonal and annual samples are given in the caption, which emphasis on the existence of a linear correlation between the two parameters. It also means that a joint probability distribution between the energy and power samples might better capture variations in the two random parameters. While the correlation coefficients of the seasonal and annual values are fairly close, slope of the line is not similar in all seasons. Therefore, accuracy of the modelling (in terms of joint DF or cumulative distribution function (CDF)) will essentially improve if data is partitioned seasonally.

Besides power, rate of change of power (RoCoP) has significant impacts on the battery lifetime. This is a well-known fact that highly fluctuating charge and discharge regime can degrade battery faster [29]. RoCoP for every unique incident is calculated in this study, seasonal and annual histograms of which are shown in Fig. 7a and 7b, respectively. Negative values show a drop in power with respect to the previous time instance. It can be seen from Fig. 7 that the number of incidents close to zero is disproportionately bigger than other range of values (i.e., bins), which could be another evidence supporting hybrid energy system application. The application can further be justified by the observation made from Fig. 6, in which low-energy incidents correlate with low-power magnitude most of the time.

General statistics of the RoCoP samples are given in Table 3 for seasonal and annual data. It can be seen that RoCoP can be as high as nominal power of battery. This sort of power fluctuation is strenuous on the battery with significant consequences on its lifetime. Similar to the energy and power samples, the largest RoCoP values occur in summer. However, the average and SD values are bigger in spring. That being said, winter with highest Skewness and Kurtosis is the most unpredictable season for the RoCoP modelling, which is similar to what have been observed for the energy and power samples.

Table 3: General statistics of RoCoP samples (in kW/min) during `Delta Solar` mode.

Season	Maximum	Average	SD (σ)	Skewness	Kurtosis
Autumn	265.3	83.0	101.95	0.202	2.57
winter	296.0	82.13	102.69	0.254	2.80
Spring	293.98	96.09	118.7	0.22	2.40
Summer	307.08	95.49	114.89	0.21	2.37
Annual	307.08	89.33	110.05	0.22	2.54

To finalise super-capacitor sizing from Section 4.1, power requirement of the hypothetical super-capacitor is calculated. Nominal power of super-capacitors is specified in kW/kg. This value changes from one model and manufacturer to another. Therefore, power sizing of the super-capacitor depends on the specific model that is going to be used in an application. If it was intended to use a BCAP0650 super-capacitor (650 F) from Maxwell Company [30] for the Gatton plant, which has specific power of 6.8 kW/kg and each cell is about 200 g, it can handle power up to 369.9 kW which is higher than maximum power of each battery inverter and bank. Moreover, the maximum power incident over a year never exceeded 331.2 kW (according to Table 2), which is still below nominal power of the super-capacitor. Therefore, power as well as energy requirements can be fulfilled by selecting BCAP0650 super-capacitor from Maxwell company. According to [30], the price of this model of super-capacitor is about AU$57 per cell and the overall cost of the super-capacitor for this application will be less than AU$16,000. Please note that the cost of power electronic interface and controller is not considered.

4.3. Battery SOC

Battery SOC at the end of each ramp-down event is another important parameter in the battery health and sizing studies. SOC values are shown in Fig. 8 at the end of each unique event for different seasons as well as the whole year. General statistics of the SOC samples are also reported in Table 4 for different seasons and annual data. In general, the battery SOC is well-maintained within an acceptable range in different seasons. The maximum SOC is almost the same in all seasons and it is very high. It shows that there are low energy events which might be better to be covered by other storage devices, such as super-capacitor. In summer, we have the best operation scenario for battery since the SOC values never go below 65% and the average SOC is the highest at about 85%. In this case, the battery will be ready for the future events in terms of available energy . It is anticipated because summer has the highest amount of solar irradiation and longer daylight hours so that battery has more opportunity to be charged. High average SOC also implies a better operational practice for the battery with less health implications. Other seasons experience low SOC levels (less than 30%) in multiple occasions. Autumn and winter have the lowest average and minimum SOC. This is undesirable to discharge the battery below 20% because of its adverse impact on the battery lifetime. This problem can be mitigated by changing current operational practice to charge battery more often in these seasons. Despite other parameters which had positive

Skewness, the battery SOC shows negative Skewness, which implies a longer tail on the left. This is because of low SOC incidents in the samples.

Table 4: General statistics of battery SOC samples (in %) during `Delta Solar` mode.

Season	Maximum	Minimum	Average	SD (σ)	Skewness	Kurtosis
Autumn	99.0	9.9	75.7	14.45	-0.71	4.09
winter	96.6	15.2	73.86	14.24	-0.71	3.85
Spring	97.5	22.4	82.24	9.14	-1.18	6.21
Summer	98.6	65.2	84.72	7.19	-0.17	2.25
Annual	99.0	9.9	79.11	12.46	-1.13	5.20

Figure. 9 shows the seasonal and annual histograms of the SOC experimental data and the best DF fitted. Most of the values are in the upper range of SOC, which is good for battery health. While there was always a single DF, which could accurately model the seasonal and annual data for the energy and power samples, different DFs found to model SOC experimental data the best. Furthermore, the energy and power experimental data were fitting well on unimodal distribution. However, the SOC samples, specially in autumn and winter, represents bimodal distribution with two peaks. Nevertheless, the importance of data partitioning (specifically based on different seasons) can be realised from SOC histograms. For histogram and DF fitting, data are centred around their average value because it yields better fit. The average SOC was 79.11% from all available data.

4.4. Time Gap

After every ramp-down incident, the battery energy will reduce. Hence, there should be enough time to charge the battery for the future events if battery energy is depleted. It will have significant consequences in the sizing and operation studies. For instance, if incidents are too close, it leads to a larger battery capacity to cover next incident in line. The time gap between two events can be problematic when it is too short to charge the battery until the next event. It depends on the battery SOC at the beginning of every event, capacity of the battery, and the energy required for the next event, $f(SOC_{init}, E_{batt}, E_{next})$.

To analyse this parameter, the time difference between the unique events is calculated from the data, general statistics of which is reported in Table 5. The first event of every day is not considered in this analysis. The maximum time gap in winter and spring are larger than their counterparts in other two seasons. However, the average time gap is larger in autumn which implies fewer incidents throughout the season. The time gap in winter is more stochastic because of high Kurtosis value. This observation suggests different operation algorithms for battery in different seasons to improve the battery performance and health. The 50$^{\text{th}}$ percentile of the time gap samples is 5 minutes, which means that the time gap is 5 minutes or less for 50% of the time. This could have significant impacts on the battery sizing and operation studies. Similar to the energy and power samples, the time gap can be best modelled with "Generalised Pareto" DF for every season as well as the annual samples.

Table 5: General statistics of time gap samples (in minute) between consecutive events during `Delta Solar` mode.

Season	Maximum	Minimum	Average	SD (σ)	Skewness	Kurtosis
Autumn	370	2	16.1	33.4	6.3	53.8
Winter	388	2	12.1	26.2	7.7	81.6
Spring	400	2	12.8	27.8	7.2	74.5
Summer	367	2	13.0	27.0	7.2	74.0
Annual	400	2	13.4	28.8	7.1	69.5

4.5. PV-side Ramp-Rate Analysis

So far, only ramp-down control was investigated using battery operation data, where commands sent by the CSS has been followed by the battery inverter controller. The observations presented in this subsection could be useful in battery sizing studies, which typically starts from predicting PV plant. To do the analyses, data are collected for each PV string, shown in Fig. 1, on both DC and AC sides of the inverters. Ramp-rate for the entire PV generation is limited to 10 kW/s (i.e., 600 kW/min). To analyse PV strings individually, ramp-rate limit is divided between five arrays according to their rated capacity. Values are normalised based on the maximum power on the DC side of the inverter, i.e., 684 kW, for comparison purposes. Also, total PV plant production is simply calculated by adding generation of the five PV arrays.

As expected, there is 100% correlation between DC and AC values of every inverter. The number of ramp-rate violations, maximum, average of absolute values, and SD of violations are plotted in Fig. 10 for every PV array and the overall plant. Values are given for both DC and AC sides of every inverter for comparison.

Following observations can be made from Fig. 10:

- For all PV arrays and the overall plant production, it can be seen that the ramp-rate violations on the DC side is always more than the AC side of the inverter. This is mainly caused by the inverter losses and reactive power compensation, as explained in Section 2. In the battery sizing and operation studies, these factors are typically ignored.

- PV plant smoothing effect can be realised from the figure where the number of ramp-rate violations, maximum, average, and SD of violations are significantly less for overall plant production compared to the individual PV array performance. In theoretical studies reported in the literature, the model of a single PV module is usually used to generate PV power time series from solar irradiation and ambient temperature data to calculate ramp events. It is clear from Fig. 10 that neglecting smoothing effect in those studies leads to wrong decisions, e.g., over-sized battery capacity in sizing studies.

- SA and DA arrays have the largest maximum ramp incidents. Also, the average ramp-rate violations is the highest for the SA and DA arrays. It shows that although advanced tracking systems increase overall generation in the plant, they require more efforts to control ramping events (e.g., larger storage).

- “Generalised Extreme Value” DF found to be the best for modelling the ramp-rate events (combination of ramp-up and ramp-down). Therefore, using normal distribution for such application will lead to significant error in calculations and modelling.

- The maximum ramp-rate violation can be as high as the rated capacity of the individual PV array. For the overall plant, it is still higher than 85%, which is significant. Additionally, the average ramp-rate violation for the overall plant is not significantly different from the individual arrays. While the smoothing effect can reduce the number of ramp events, it might not be as much effective during large ramping incidents.

- Compared to the maximum ramp-rate violations, the average and SD values are relatively small. It proves that severe ramping incidents rarely occurred. Therefore, appropriate statistical model of the ramp events is needed to properly size and operate battery.

Ramp-up and ramp-down incidents are separately analysed in Fig. 11 for the AC side of the inverter for all PV arrays. The following insights can be inferred from the experimental data shown in Fig. 11:

- Despite the PV inverter effort to regulate ramp-up events and reactive power compensation, the number of ramp-up incidents is significantly more than ramp-down ones in the individual arrays. It suggests that the ramp-up events happen more often than the ramp-down ones. It will have consequences in the battery sizing and operation studies.

- While both ramp-up and ramp-down events are considerably reduced at the entire plant level, the smoothing effect has more impact on the ramp-up incidents compared to the ramp-down events.

- Although the number of incidents is more for the ramp-up events, maximum, average, and SD of violations for all cases occurred during the ramp-down incidents. Higher average of the ramp-down events means that the battery is more likely to be discharged rather than charged. Therefore, battery should always maintain a high level of charge to be able to ride through the ramp-down events by being regularly charged.

- The previous observation also shows that ramp-up and ramp-down events are not energy neutral, i.e., accumulated charged and discharged energy during ramping incidents are not equal. Therefore, the battery operation algorithm should take this into account by regularly charging the battery.

- It can also be seen from Fig. 11 that SD is bigger for the ramp-down events, which makes it less predictable.

These observations are useful for the next generation of the sizing studies and designing battery operation algorithms.

5. Conclusion

This paper offers thorough analyses of the battery operation under ramp-down control mode within a medium-scale PV plant. One year of field data is used to draw insights from the battery operation, which could be useful for the battery sizing and operational studies in the future. Investigations are carried out for the different parameters of the battery operation. It has been shown that seasonality has an impact on the ramp events, which consequently affect the battery operation in different ways, such as SOC level. As a result, statistical model of different parameters are more accurate when modelling is carried out on the seasonal data. According to the statistical analyses, the battery energy is more predictable compared to the battery power, while there is a strong correlation between the two parameters. The application of super-capacitor is also assessed, which showed that it can improve battery lifetime and the economic operation of the whole plant. Analysing parameters such as the time gap between two consecutive events revealed that they should be considered in the sizing and operation studies.

Finally, investigation on the ramp events on the DC and AC sides of the PV inverters shows that using theoretical model of PV module without accounting for smoothing effects in medium- and large-scale PV plants, inverter operation for reactive power consumption, system-wide losses, etc., can lead to wrong decisions in the sizing and operation studies. It is also shown that smoothing effect is not an ultimate solution to the PV ramp-rate problem.

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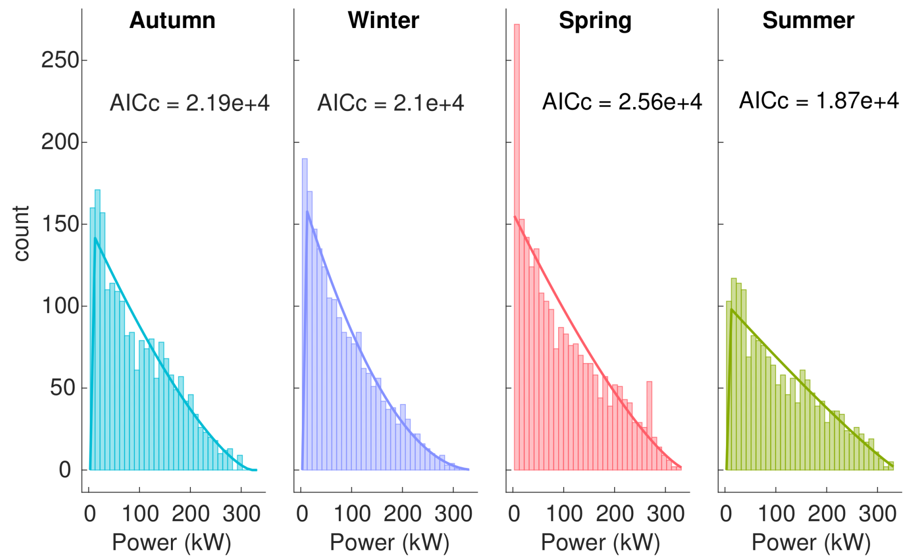
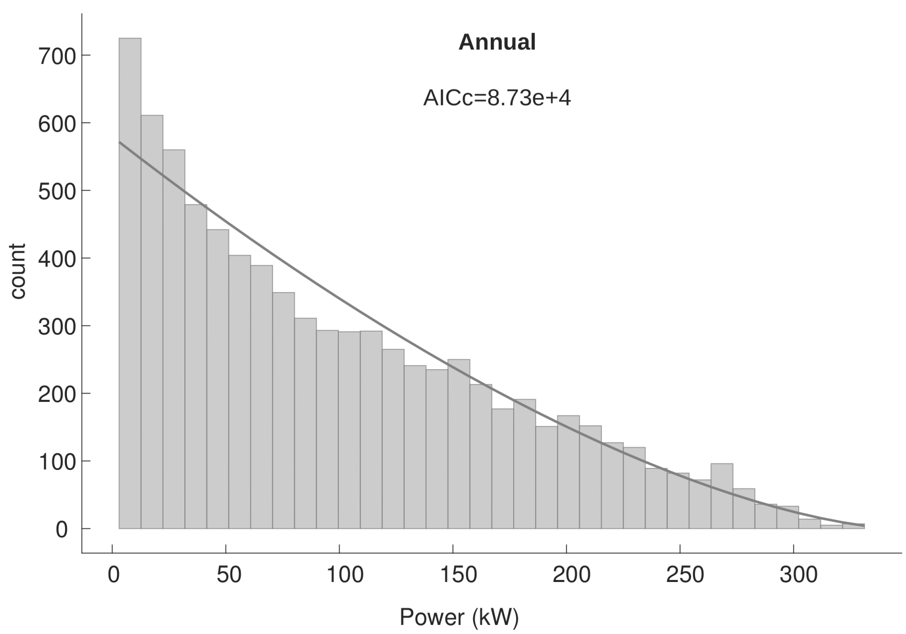


(a) Seasonsal



(b) Annual

Figure 5: Histogram of the battery power samples during `Delta Solar` mode

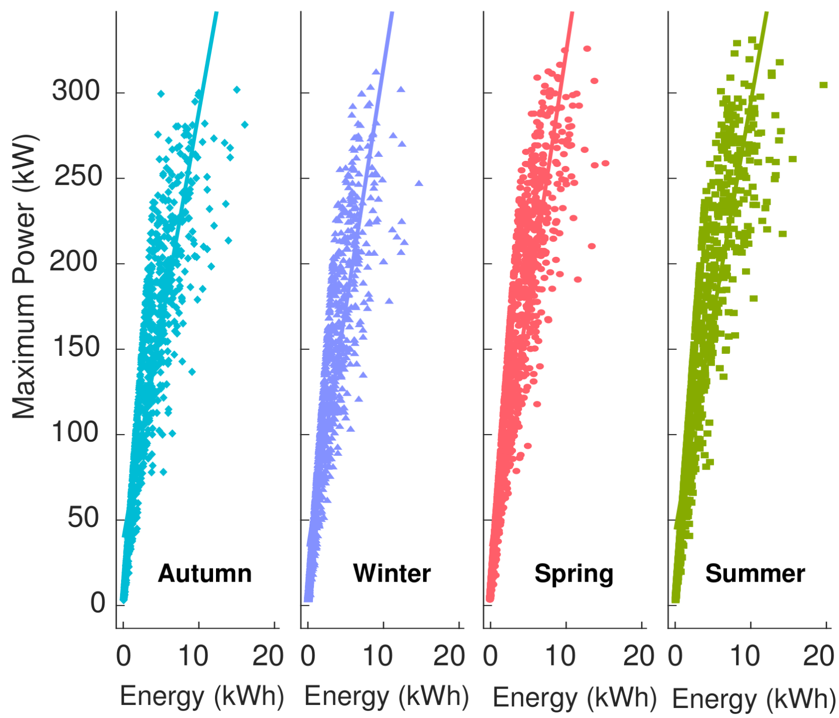
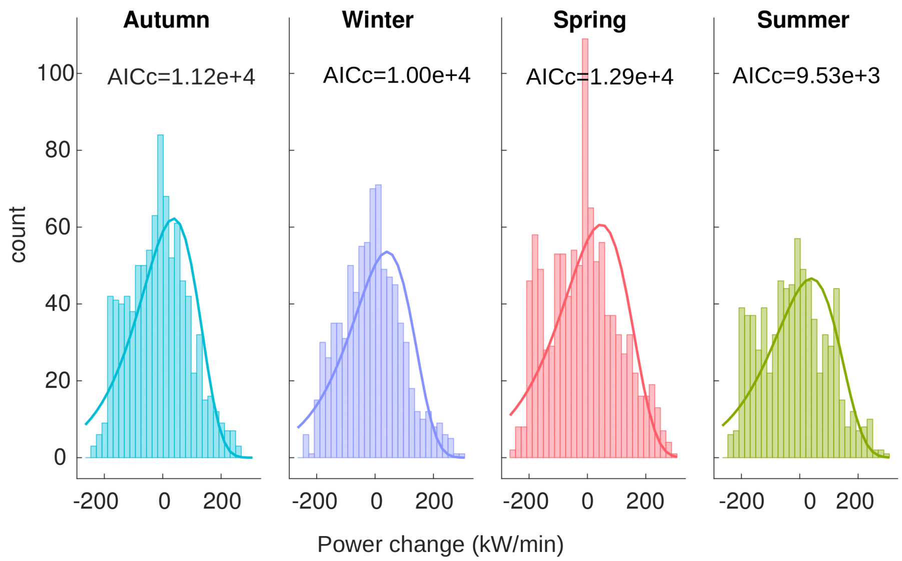


Figure 6: Maximum power vs. energy of every unique incident– Seasonal (*correlation coefficient* (ρ) is 0.88, 0.885, 0.893, and 0.906 for autumn, winter, spring, and summer, respectively) and Annual (ρ is 0.891)



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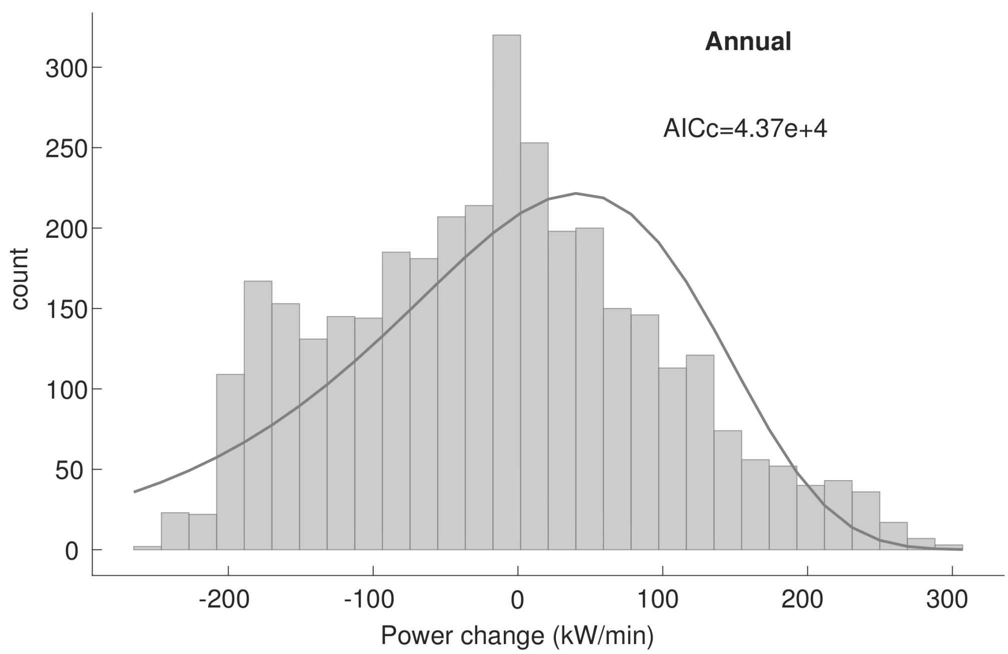


(b) Annual

Figure 7: Histogram of RoCoP samples (kW/min) without outlier

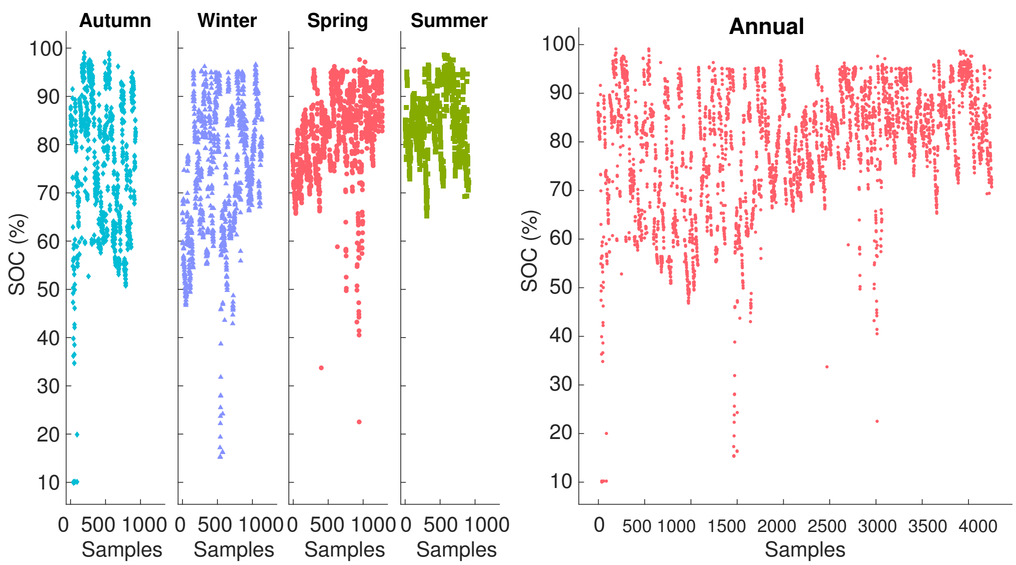
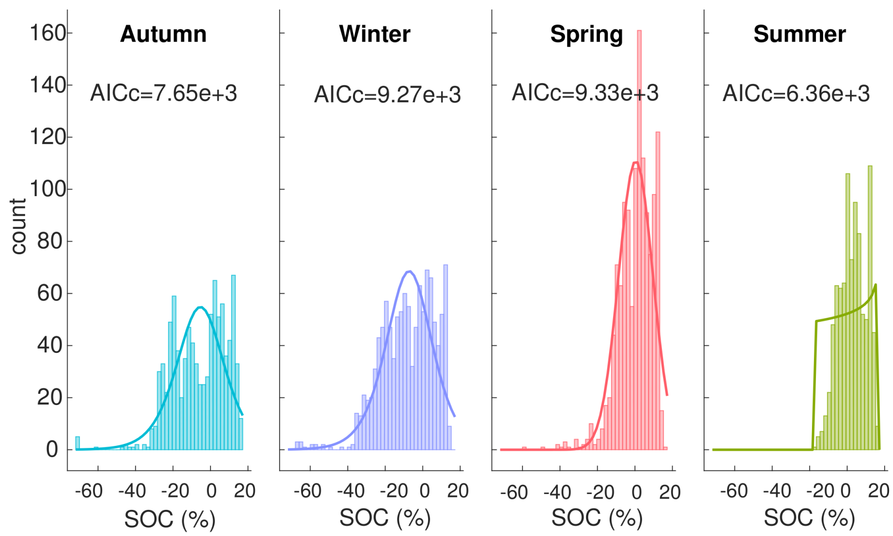
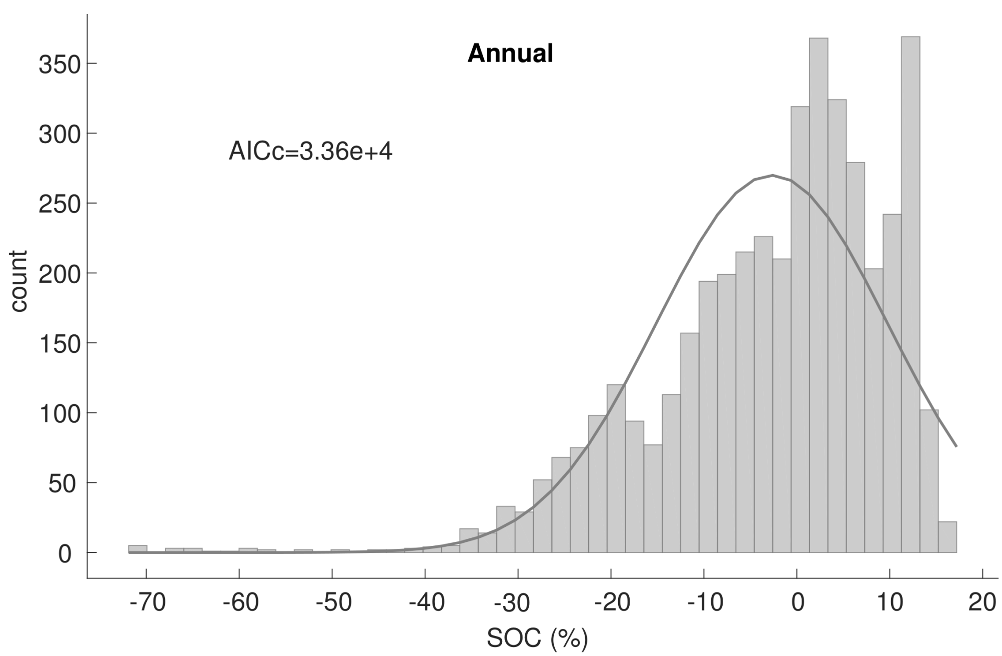


Figure 8: Battery SOC at the end of each unique `Delta Solar` event



(a) Seasonsal



(b) Annual

Figure 9: Histogram of the Battery SOC samples without outlier [Fitted PDF for Autumn: *Logistic*, Winter: *Logistic*, Spring: *Normal*, Summer: *Generalised Pareto*, and Annual: *Normal*]

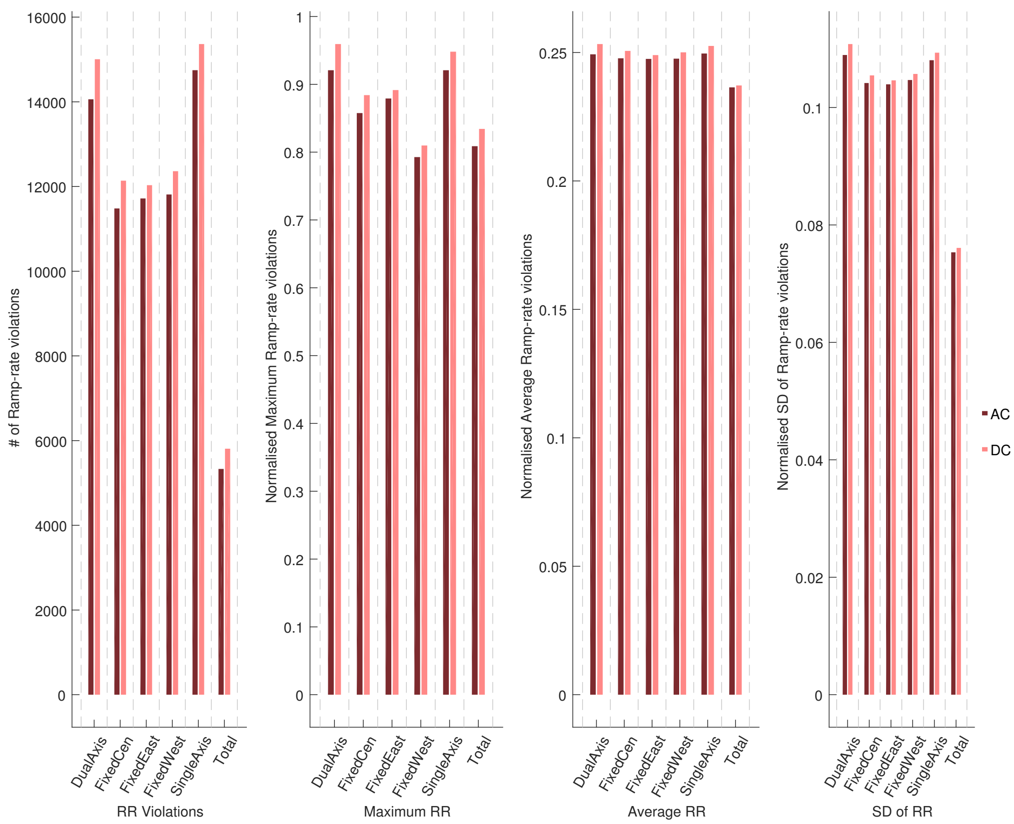


Figure 10: Ramp-rate violations for all PV arrays on DC and AC sides of inverters

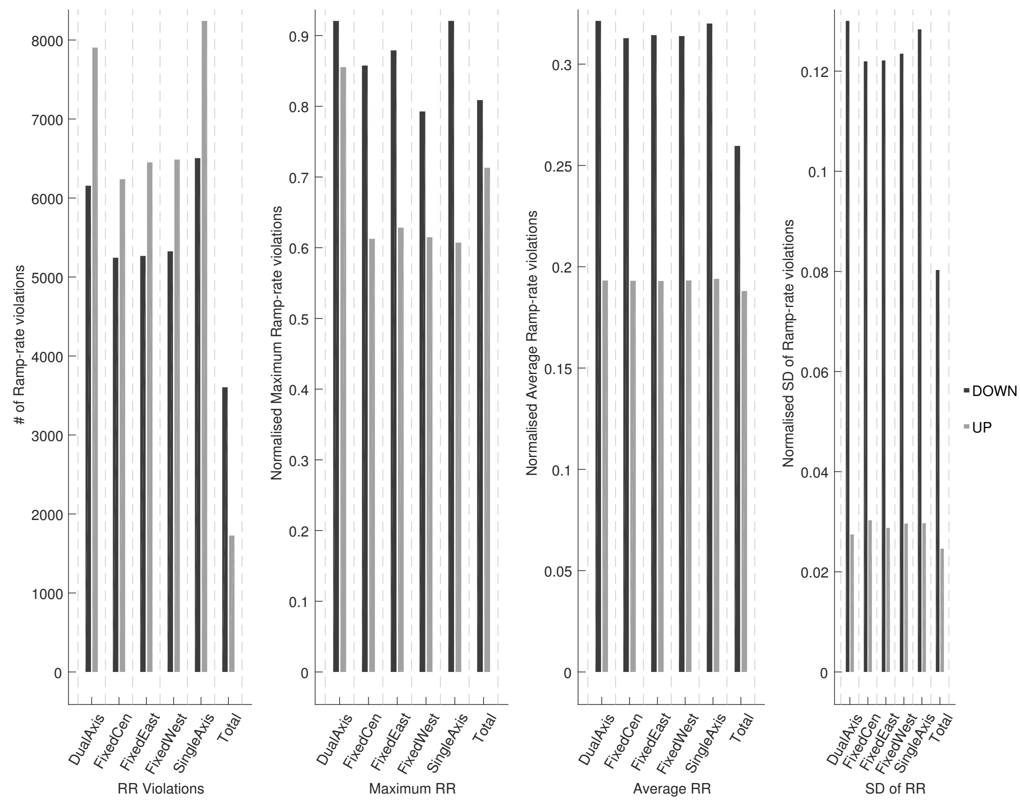


Figure 11: Ramp-up and ramp-down violations for all PV arrays on the AC side of inverters