



An energy storage algorithm for ramp rate control of utility scale PV (photovoltaics) plants

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ABSTRACT

Balancing authorities are currently exploring options for preventing potential increases in ramping costs of conventional generators in the grid by setting ramping limits on variable energy resources. In this paper, we present the methodology and results of simulations on the smoothing performance of battery, flywheel and ultra-capacitor energy storage technologies connected to single large-scale PV (photovoltaics) plants subject to a 10%/minute ramping limit. The simulations were run using second-to-second output data of four large-scale PV plants of which two are in the Southeast of Canada (5 MW and 80 MW) and two in the Southwest of the US (21 and 30.24 MW). Energy storage units are sized for each plant on a baseline of 99% violation reductions and their performances are compared. We also present two dispatch strategies tailored to low and high cycle-life storage technologies which are modeled without forecasting measures and assuming perfect short-term forecast for the remainder of the averaging period.

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1. Background

The primary challenge of integrating large amounts of solar power into the electricity grid lies in the solar resource's variability. In their continuous effort to balance supply and demand, grid authorities have expressed concerns especially about fast, cloud induced ramps of large-scale solar PV plants. Several studies have shown that this variability greatly reduces when multiple plants' output is summed, analogous to aggregating uncorrelated demands. Our previous work was focused on assessing minute-by-minute variability due to cloud movements of single utility-scale PV plants, ranging from 5 to 80 MWac nameplate capacities. Supported with empirical data we showed that short-term ramp rates become attenuated even within a single plant as the size of the plant increases. We expanded on this study with higher frequency (second by second) data and assessed the magnitude of power fluctuations at a variety of timescales and plant sizes (currently up to 250 MWac).

After plant variability was understood and quantified, we are now investigating operating algorithms of ESU (energy storage

units) to perform ramp rate control at the plant level. The rationale for this are the emerging concerns and proposed plans of grid balancing authorities to deal with ramps of variable energy resources (i.e. solar and wind): The PREPA (Puerto Rico Power Authority) has recently included a ramp rate limit to their requirements for large-scale PV facilities; currently this limit is 10% of the rated capacity per minute although PREPA has not yet disclosed full details of the regulations [1]. Also, the California ISO is currently working on a market-based solution for ramps called the 'Flexible Ramping Product' where costs will be allocated to generation and load in accordance with cost causation principles [2]. ESUs can be used to mitigate penalty fees from ramps and even allow for additional revenue streams by participating in other grid balancing markets (e.g. frequency regulation). This study aims to: 1) build and optimize an ESU dispatch model; and 2) determine the size of ESU needed for four plants in different locations to mitigate 99% of violations compared to the baseline scenario of having no ESU installed.

1.1. Geographic dispersion

In studying the effect of PV systems on the grid, we must consider variability in the output of all grid-connected PV systems located in a system operator's service area. Several studies have

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detailed the effect of geographic dispersion on the output variability of many smaller systems or irradiance sensors. For example, Wiemken et al. [3] found that the highest 5 min ramp rate for a single system was 52% of system capacity, while 100 systems, together totaling 243 kW, showed ramp rates up to only 5% of the total capacity. Murata et al. [4] introduced the term ‘output fluctuation coefficients’ as the ratio between the maximum observed ramp rate in a certain time window, over the standard deviation of ramp rates in that same time window. As the number of systems increases, the coefficient reaches an asymptote depending on the width of the time window, and the season. Besides that, pair-wise correlations of PV-system ramp rates were derived from the data; they were shown to be close to zero, even for distances around 50 km. In fact, 1 min correlations of step-changes already had declined to 0.12 for two inverters within a single plant [5].

As ramp rate correlations on a per-minute basis drop significantly over sub-km distances, multi-MW PV systems also exhibit some degree of geographic dispersion. In fact, when plants extend beyond the size of fast-moving cumulus clouds, variability is reduced as the clouds cover only part of the plant. Another effect is that clouds often do not move fast enough to completely cover a plant from one time interval to the next, as we discuss later in this section. With a 290- and 500 MW-plant under construction, it is important to assess what variability can be expected from them. Other multi-MW plants were shown to exhibit extreme (minute) ramp rates of up to 50% for a 4.6 MW system [6], and 45% for a 13.2 MW system on a ‘highly variable day’ [5]. Kankiewicz et al. assessed variations in the output of a 25 MW 2-axis tracker system in Florida, recording minute-averaged ramp rates of up to ~20% during a single day’s output [7]. However, the outputs of these PV plants can not be directly compared as the systems differ in shape, size and panel orientation.

Hoff and Perez took a different approach in quantifying PV output by using satellite imagery, which allows for the collection of data for a large number of points on the map [8]. Their model showed that the Relative Output Variability for a fleet of PV systems is a function of the number of systems and the Dispersion Factor. The Dispersion Factor is a dimensionless variable capturing the relationship between PV fleet length (L), cloud velocity (V), and the used time interval (Δt).

Lave et al. introduced an alternative method of quantifying cloud-induced variability by applying wavelet decomposition of a clear-sky index time signal [9]. They quantified the Variability Reduction on different timescales ($VR_{\bar{t}}$) of a 48 MW plant versus that of a single irradiance sensor. The same theory was then applied in their WVM (Wavelet Variability Model) to turn a single irradiance sensor’s data into simulated 48 MW-plant power output, for which the WVM was able to reproduce maximum ramp rates for 1, 10, 30 and 60 s timescales with errors <20% [10].

The data-sources in our study are First Solar PV plants that are constructed in a uniform MW-array approach, so it is possible to describe the effect of geographic dispersion at a single site for different sized sub-plants. Similar to [7] and [11], where variability was described for a stepwise increasing amount of capacity, our study employed an ‘inverter shells method’ [12], wherein variability was described with an increasing number of 0.5 MW inverters.

1.2. Energy storage dispatch

In grid systems with ramping limits like Puerto Rico, large-scale PV plants need measures to reduce their ramp rates. Upward ramps can be mitigated when sophisticated plant control systems can curtail energy during the upward ramping event. Downward ramps are more problematic as no plant controls can counteract the lack of irradiance. However, with short-term forecasting technologies like

the Total Sky Imager, energy can potentially be curtailed prior to the downward ramp so that the resulting power decrease is within the set ramping limits. Another option is to use a form of energy storage, which can deal with both upward and downward ramps by providing an energy buffer before the point of interconnection to the grid. Perez et al. (2013) report that operational mitigation of ramp rates across multiple time and spatial scales can be achieved at a cost amounting to less than 10%–15% of a PV installation [13]. Their estimates show that this cost was dependent upon the availability of solar forecasts that could be used to control the operation of the intermittency absorbing buffers.

Fthenakis et al. (2012) present a comprehensive reviews of applicable ESU options [14]. After analyzing the degree of variability at large-scale PV plants, we are now looking into the technical and economic feasibility of installing an ESU (Energy Storage Unit) at a PV plant for ramp rate control, as shown in Fig. 1.

Previous work shows that energy storage ramp rate control for solar PV requires a high power-to-energy ratio; thus it can be considered a ‘power application’ as opposed to load peak-shaving which is considered an ‘energy application’ [15]. This can be demonstrated when we consider a transient cloud over a large-scale PV system, the power output can drop rapidly from nameplate capacity to the level of output we can expect from diffuse irradiance alone (p_{shaded} , ~0.1–0.2 p.u.). With RR (ramp rate) and nameplate capacity (P_{cap}), we can describe this in a simplified equation as follows:

$$P_{PV}(t) = \max[P_{cap}(1 - RR \cdot t), P_{cap} \cdot p_{shaded}] \quad (1)$$

If the PV plant is subject to a ramp rate limit (RR_{lim}), the desired output (including support from the ESU) would be:

$$P_{PV+ESU}(t) = \max[P_{cap}(1 - RR_{lim} \cdot t), P_{cap} \cdot p_{shaded}] \quad (2)$$

The ESU power required during this event is naturally:

$$P_{ESU}(t) = P_{PV+ESU}(t) - P_{PV}(t) \quad (3)$$

Using (1), (2) and (3) we can solve for the maximum

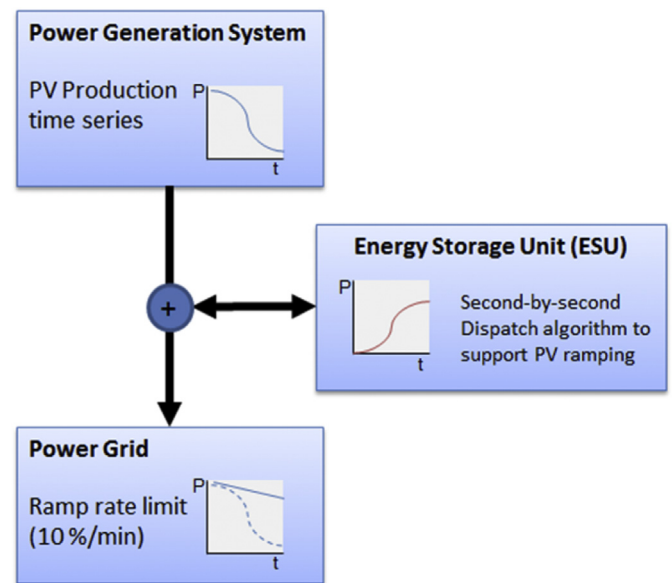


Fig. 1. Schematic of the interaction between a PV plant and an energy storage unit to comply with ramp rate limits at the POI (Point of Interconnection) with the grid, set by the power authority.

instantaneous power and total energy delivered, which are needed for sizing the system.

$$P_{peak}[MW] = P_{cap}(1 - p_{shaded}) \left(1 - \frac{RR_{lim}}{RR} \right) \quad (4)$$

And the Total Energy required:

$$E_{ESU}[MWh] = P_{peak} \left(\frac{1 - p_{shaded}}{2RR_{lim}} \right) \left(\frac{1hr}{60min} \right) \quad (5)$$

Fig. 2 shows a hypothetical ESU dispatch for an 80 MW plant with $p_{shaded} = 0.15$ p.u., $RR_{lim} = 0.1$ p.u./min and $RR = 0.25$ p.u./min. The total energy capacity delivered by the ESU during this event is 2.9 MWh, while its peak power output amounts to 41 MW. This translates into a P:E ratio of around 14.

In actuality, the time series power output of a PV plant does not obey the linearity shown in Fig. 2 due to the dynamic and complex nature of clouds. For this reason, we wanted to investigate ESU dispatch using actual PV plant power output time series.

2. Dispatch algorithm

The goal of this research is to design a dispatch algorithm for different ESU technologies to control PV ramp rates, assuming there is a ramp rate limit (RR_{lim}) of 10%/minute. A violation will be counted at the end of each minute if the power average over that period differs more than 10% of plant nameplate capacity from the last minute's power average.

The simulation will happen 'real-time' with second-by-second time steps, so in determining the ESU dispatch decision, no data beyond the last second are used. A crucial factor in this analysis is short-term forecasting, as ESU-dispatch could be improved if PV output for the remainder of the period was known. We therefore define the following scenarios: 1) assuming we know nothing about future power output and 2) assuming we know exactly what the future output on the remainder of the 1 min period will be (perfect forecasting). In order to make sensible projections on output in the first scenario, we use a linear extrapolation of recent (10 s) power output [16].

2.1. Algorithm structure

The ESU dispatch algorithm was built using a modular approach so that the performance of elements in the model can easily be tested and compared with alternatives such as different dispatch

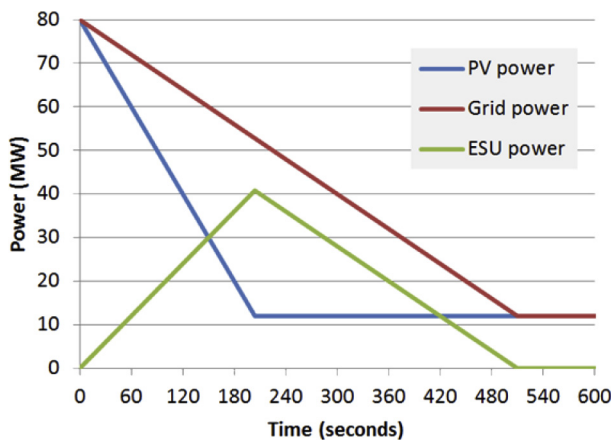


Fig. 2. Example cloud transient event where a 0.25 pu/min sustained ramp rate is adjusted by an ESU to meet the 0.1 pu/min ramp rate limit. The required ESU power and energy capacity are ~41 MW and 2.9 MWh.

strategies (Dynamic Rest and Rest Recover), which will be explained later. An overview of the model is shown in Fig. 3.

The algorithm cycles through a second-by-second time series of raw PV plant power output and decides on the dispatch of the ESU. Information is logged for several parameters in the model:

- PV Power (P_{PV})
- ESU Power – after losses for discharging, before losses for charging (P_{ESU})
- Grid Power ($P_{GRID} = P_{PV} + P_{ESU}$)
- ESU inefficiency losses ($P_{loss ESU}$)
- ESU State of charge (SOC_{ESU})
- Moving average of period – PV power ($P_{movavgPV}$)
- Moving average of period – Grid Power ($P_{movavgGRID}$)
- Power limits (P_{lim-up} and $P_{lim-low}$)

The objective is to minimize the number of ramp rate violations ($>10\%/min$) while keeping the load on the ESU and lost energy due to charge/discharge inefficiencies at a minimum. Using the model, we simulated different energy storage technologies to get a performance comparison by varying a number of parameters related to the ESU (e.g. self-discharge rate, lifetime and charge/discharge efficiency).

2.2. ESU technologies

In this paper, we present the results from simulations of five different ESU technologies (li-ion and lead-acid batteries, two types of flywheels and ultra-capacitors). The characterizations of these, which are used in our model, are shown in Table 1.

2.3. Flywheels

Flywheels are mechanical devices that store energy in the form of rotational (kinetic) energy. When net torque is applied in the direction of angular velocity (for example by an electric motor), energy is stored. Energy is released when reverse torque is applied and can be recovered with the same electric motor acting as a generator. Specifications used in this study are from a commercially available flywheel storage system that is developed by Beacon Power (now acquired by Rockland Capital). Their devices have been operating in at least one grid-connected flywheel storage plant. Compared to batteries, they have a relatively high cycle life and power-to-energy ratio and therefore seem a good candidate for this power burst smoothing application. However, their self-discharge rate is significant and increases proportionally with angular velocity squared, which suggests keeping its SOC (state of charge) low when possible [20]. In this study we simulated two flywheel systems with different P:E ratios, both manufactured by Beacon Power.

2.4. Li-ion and lead-acid batteries

Batteries store energy in the form of chemical energy. The most widely used chemistries of batteries are lead-acid and lithium-ion, which are most used in respectively vehicles and portable electronics. Due to the batteries' low cycle life, it is desirable to minimize usage of the battery when possible. Extremely low and high SOC levels should be avoided as well. Their power-to-energy ratio depends on the internal design (for lead-acid: thickness of the plates) and is in trade-off with the battery lifetime (thinner plates have higher output but shorter lifetime). As of now, the algorithm assumes efficiency is constant (independent of charge/discharge rate) but future algorithms will

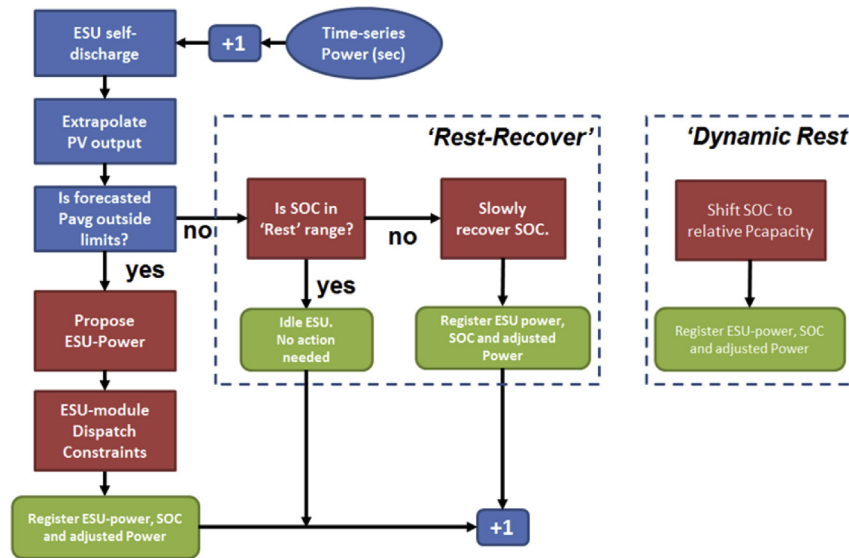


Fig. 3. Decision diagram: the algorithm cycles through the time series and calculates an ESU power dispatch in case the ramp rate is expected to exceed the ramping limit. The dashed boxes show two variations of dispatch strategies that suit low cycle-life and high cycle-life energy storage technologies.

include more detailed efficiency considerations like the KiBaM model [21].

2.5. Ultra-capacitors

Ultra-capacitors, also known as supercapacitors, are devices that store energy in the form of electrochemical energy by separation of charge carriers between two active electrodes. The electrodes are separated by a layer of porous, activated carbon with a large surface-area to increase capacitance and a thin, ion-permeable insulator to prevent short-circuiting. Similar to batteries, multiple of these can be connected in series to step up the voltage. Like flywheels, ultra-capacitors have a characteristic high power capacity that makes them suitable for ‘burst applications’ – high power for short durations. Also, they have a long life and can handle hundreds of thousands of full charge–discharge cycles. Device specifications were retrieved from Maxwell, a manufacturer of ultra-capacitors for various applications [22]. Like batteries, their charge and discharge efficiency depends on how fast they are charged or discharged [23].

2.6. Dispatch strategies

Considering the big range in cycle-life and P:E ratios of the ESU technologies described above, we developed two separate strategies for dispatch algorithms: 1) RR (Rest-Recover) and 2) DR (Dynamic Rest). The Rest Recover strategy is tailored to low cycle-life technologies like batteries, as it minimizes ESU usage. It employs a

SOC range of 40–60% in which the battery is on stand-by for possible upcoming ramps. After the battery is used for a ramping event it will gradually be brought back to this range to get it ready for the next event. In contrast, the Dynamic Rest strategy is fit for high cycle-life ESUs (e.g. flywheels and ultra-capacitors) as it has the ESU's SOC level actively following the PV plant's relative output. This will result in a more effective use of the ESU's limited energy capacity, which is useful for high P:E ratio devices. For example, when the PV plant is operating at 100% of its nameplate capacity, the ‘rest state’ of the ESU is at 100% SOC. At this time, only downward PV output ramps are possible so it is best to keep the ESU fully charged. At nighttime, PV output is zero, so the flywheel is at 0% SOC, preventing unnecessary self-discharge losses.

3. Data

Simulations for all ESUs were run on data from four large-scale PV plants of which two are in the Southwest of the US (21 and 30.24 MW) and two are in Ontario Canada (5 and 80 MW). For each plant, two years of second-by-second power output data were collected. Some data errors were found and filtered out from the simulated data set. It was previously shown [12] that each of these plants yield per-minute ramp rates of up to 0.43, 0.53, 0.65 and 0.7 times their corresponding capacity. Due to the effect of geographic dispersion we can expect a decrease in the ramps exceeding 10% per minute with increasing plant size, thereby decreasing loads on ESUs.

Table 1
Overview of Energy Storage Units simulated in this study.

Technology	Flywheel [17]	Flywheel [17]	Ultra-capacitor	Li-ion battery	VRLA battery
Type	Beacon Power	Beacon Power	Maxwell	Lithium Cobalt Oxide	Valve Regulated Lead Acid
Acronym	‘High Power’ flywheel	‘Power & Energy’ flywheel	UCAP	Li-ion	VRLA
Charge/Discharge efficiency	0.92/0.92	0.92/0.92	0.95/0.95	0.98/0.95	0.90/0.90
Power:Energy ratio	12	4	50	2	2
Cycle Life	100,000	100,000	1,000,000 or 15yrs	1900 @80% DoD [18]	~700 @80% DoD [18,19]
Self-discharge	10% of SOC per hour	10% of SOC per hour	2% of SOC ¹ per hour	0.02% of nameplate per hour	0.0014% of nameplate per hour
Dispatch Strategy	Dynamic Rest	Dynamic Rest	Dynamic Rest	Rest-Recover	Rest-Recover

The two vastly different climates in which these plants are located can give us insights into how their variability affects loads on ESU support. However, it is important to note that the findings from this research do not apply directly to similar sized plants in any other region in the world, as the cloud dynamics in a geographic region may be completely different from what is studied here. For example, the difference in variability for three simulated 60 MW plants in San Diego CA, Oahu HI and Mayaguez, Puerto Rico was shown in a study by researchers at UCSD [24]. We do aim to apply the ‘tool’ that we designed here to other time series of data, which can potentially be sourced from single irradiance sensors after a ‘scale up’ conversion process is applied, according to a recent study [25].

4. Results

First, a baseline was established by counting the 10%/min ramp rate violations for the raw data, without an ESU to provide ramp rate control. For two years of data for each plant, we found 2500–9000 violations, which is between 0.5 and 1.7% of all minutes in the year (Fig. 4). We took the year with the most violations to carry out the rest of the simulations presented in this paper.

After these simulations, we started adding different sizes of ESU and observed the decreasing number of violations as ESU size increased.

Fig. 3 is a graph of ~240 iterations (4 min) of the model at the 80 MW PV plant in Ontario Canada, simulating a 700 kWh, 8.4 MW ‘High Power Flywheel’ utilizing the ‘Dynamic Rest’ algorithm and a 10%/min ramping limit. The plant output is leveled at 70 MW when a cloud starts covering the plant at the 1 min mark. During the second minute, P_{GRID} drops below the lower ramping limit, but the 60s-period average is still within the limits and therefore no ESU support was needed. In the third minute however, PV power continues its drop and the flywheels start discharging to bring the $P_{movavgGRID}$ right above $P_{lim-low}$, therefore complying with the set 10%/min ramping limit. In the last minute we see that the continued drop in PV power pushes the flywheel ESU to output maximum power, but it appears insufficient to prevent a violation: the $P_{movavgGRID}$ falls below the allowed ramp range.

As mentioned before, the model incorporates two different dispatch strategies (Dynamic Rest and Rest Recover), depending on what ESU technology is used. High cycle life technologies use Dynamic Rest, making better use of their often limited energy capacity, while low cycle life technologies such as batteries employ

the Rest Recover strategy so to minimize their mileage. In Figs. 6 and 7, we show about an hour of dispatch during variable output conditions with the two different dispatch strategies. It shows how the flywheels’ State of Charge on the left side is continuously following the PV plant’s output: charging when the plant ramps up and discharging when it ramps down.

For each plant, we simulated ESU performance for different energy storage capacities and plotted the number of violations as a function of energy and power capacity.

We can make an exponential fit of the violation reduction performance Y for the High Power Flywheel (P:E = 12:1) as a function of its power capacity (P):

$$Y = e^{\epsilon \cdot P} \times 100\% \quad (6)$$

Table 2 shows the resulting exponents (ϵ) and accompanying R^2 values for the trend lines fitted on each plant. All show similar profiles as the right side of Fig. 7, where ESU technologies (with P:E < 12:1) are grouped together, indicating their operations were primarily power-limited, not energy limited.

Table 2

Exponential fit (Equation (6)) parameters for violation reduction performance observed for High Power Flywheels at the four plants studied.

Plant capacity	5 MW	21 MW	30.24 MW	80 MW
ϵ	−2.143	−0.518	−0.360	−0.213
R^2	0.9898	0.9985	0.9898	0.9944

Because the PV variability depends on plant size and geographic location, we decided to iterate ESU simulations until we found the energy and accompanying power capacity at which roughly 99% of violations are prevented for each plant (Fig. 8). From equation (6), the ESU power capacity would be:

$$P = \frac{\ln(0.01)}{\epsilon} \quad (7)$$

In order to reduce ramping violations to 1% of the baseline, all technologies except ultra-capacitors showed similar power capacity requirements (right side of Fig. 8). This implies that at least up to 12:1 P:E ratio, the ESU performance is power-limited, not energy-limited. We also see that for the energy-limited ultra-capacitors (P:E ratio of 50:1), the energy capacity requirement for 5, 21, 30.24 and 80 MW plants are equal to respectively 1.7, 1.9, 1.7 and 1.2 min of full plant capacity.

For the 21 MW plant, we simulated the violation reduction performance on the other year of data for the same ESU sizes. We found a slightly higher but narrow range of violation reduction performance (99.5–99.6%) across all ESU technologies compared to the 99.0% for the first year. This percent difference amounts to an additional 15 violations over the whole year. This implies that at these high violation reduction percentages, a couple extra days with fast-moving clouds inducing high ramp rates can contribute a significant amount of additional violations in one year compared to another.

4.1. ESU mileage and losses

We calculated the total absolute State Of Charge changes of the ESU for the whole year and found large differences between the Dynamic Rest and Rest Recover strategies as expected. The Rest Recover strategy – Dispatch only when necessary – shows 26–61 and 16–50 cycles/year for VRLA and LIION, respectively. Larger P:E ratio technologies (Flywheels and Ultra-capacitors) utilizing the Dynamic Rest strategy showed 873–1708 cycles.

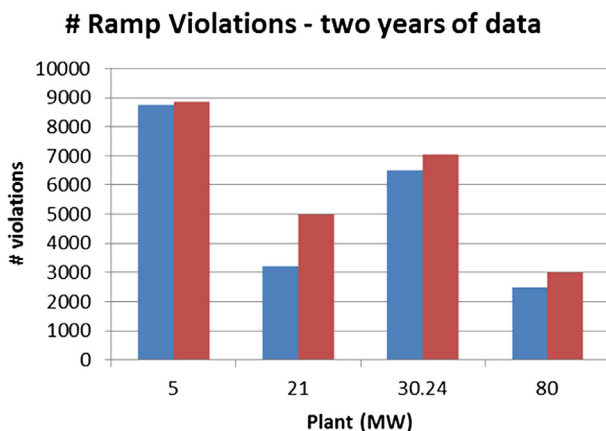


Fig. 4. Number of 10%/minute violations recorded over two years of data at four different plants.

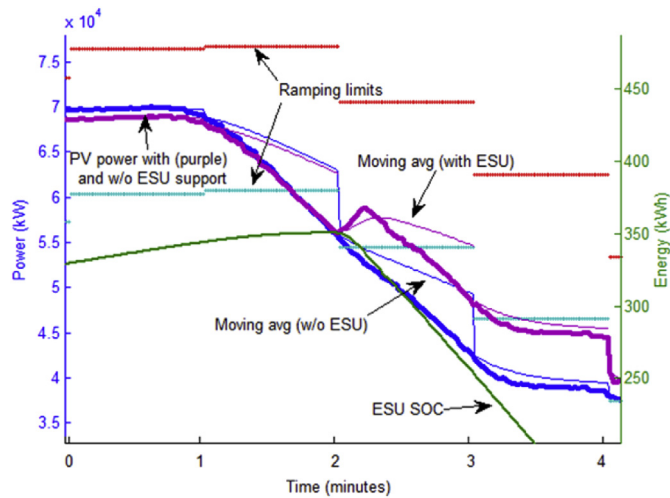


Fig. 5. 4 min excerpt from the modeled time series. The horizontal lines show the upper and lower averaging limits for each minute which are ± 8 MW of the last minute's power average. The moving averages start at the beginning of the minute period. Note that instantaneous PV + ESU power output may exceed these limits as long as the average complies with the ramping limit.

The model accounts for two types of ESU losses; the self-discharge losses (L_s) and transfer losses associated with charge/discharge efficiencies (L_t). The technologies that employ the Dynamic Rest dispatch strategy have higher mileage and therefore

higher losses than the Rest Recover strategy. For 99% violation reduction, we see that the total energy lost ranges from 0.03% (Li-ion) to 0.96% (FWPE) for the largest plant in the fleet and 0.07%–1.48% for the smallest plant (Table 4). These are percentages of AEP (Annual Electricity Production) for the year recorded.

4.2. Forecasting

All the foreshown results were gathered assuming no forecasting was in place. Instead of active forecasts, we made projections of short-term future output using extrapolations of recent (10 s) PV output. However, it would be interesting to see how dispatch performance would be affected if we had some form of forecasting in place. To find the boundary of improvement because of this we simulated a scenario of 'perfect forecast' of output for the remainder of the period. Any added form of forecasting would then perform somewhere in between the extrapolation (no forecast) and perfect forecast scenarios.

For ESUs sized to mitigate 99% of violations, perfect forecasting for the remainder of the averaging period (1 min) further reduced violations by up to 24%. In three plant-ESU combinations, perfect forecasting did not further reduce the number of violations beyond 99% (see Fig. 9).

4.3. 5%/Minute ramping limit

Another interest was to run simulations for an even stricter ramping limit (e.g. 5%/minute). For the same hypothetical 25%/

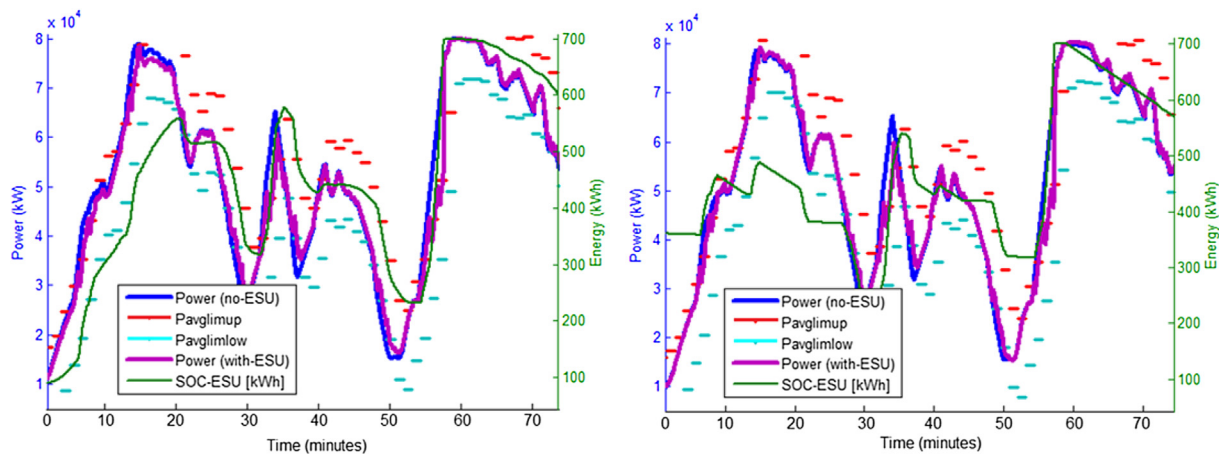


Fig. 6. Difference in ESU dispatch shown for the Dynamic-Rest (left) and Rest-Recover (right) strategies during 1 h of a variable day: August 5th, 2012. The RR puts less mileage on the ESU, but underutilizes its energy capacity range. Like Fig. 5, the horizontal red and blue lines are 60 s long. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

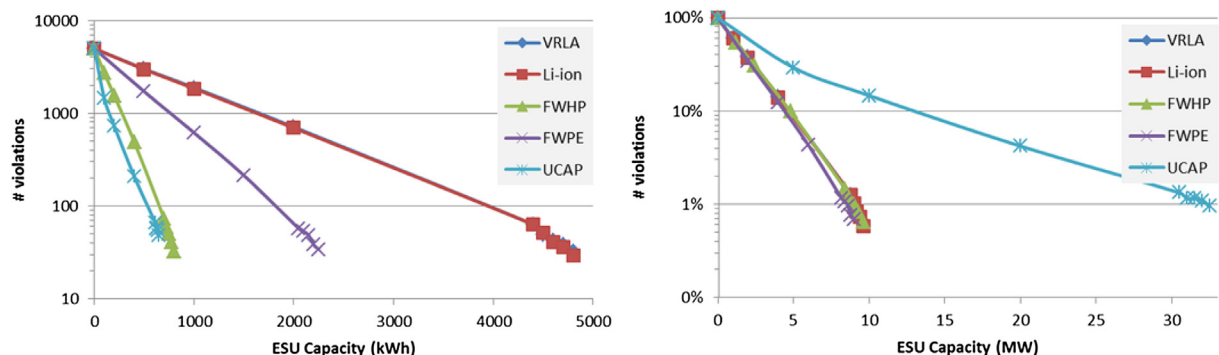


Fig. 7. Simulation results for a year of data from the 21 MW PV plant in the Southwest of the US. Left: Number of violations for different energy capacity sizes in kWh of ESUs and technologies. Right: Normalized number of violations as a function of the ESU power capacity in MW (100% = 4977 violations).

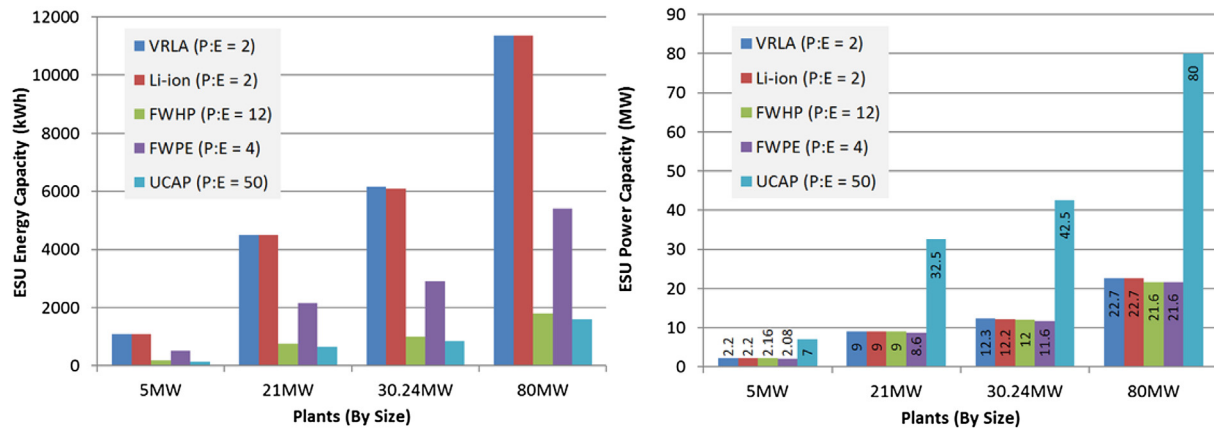


Fig. 8. Energy Storage Unit sizes for Energy capacity (left) and corresponding power capacity (right) to mitigate 99.0% of violations from the baseline scenario. All bars correspond to 99.0% reduction of violations, with the exception of the 80 MW Li-ion (99.1%), FWPE (99.1%) and UCAP(Ultra-capacitors) (99.4%) scenarios.

minute sustained PV ramp rate in Fig. 2, we would see only a slight increase in maximum ESU power demand (54 MW) but a large increase in the necessary energy capacity (~8 MWh), therefore reducing the P:E ratio to around 7:1. The performance of the different ESU technologies reflect this, as the FWHP (12:1) shows lower reduction in violations compared to the other technologies (Fig. 10).

4.4. Simple cost analysis

Cost data for energy storage units are listed in the DOE/EPRI 2013 Handbook [19] and other publications; these are summarized in Table 5.

A simplified cost analysis for mitigating a certain percent of violations can be conducted based on the cost data of Table 5, the storage power capacities shown in Fig. 8 and the equivalent full cycles performed from Table 3. Thus for mitigating 99% of the violations for the 80 MW plant, the necessary power capacity for the technologies except for ultracapacitors is approximately 22 MW (Fig. 8). With this number and the number of equivalent full cycles from Table 3, we can make a rough calculation for the total capital expense needed to perform ramp rate control using the considered technologies listed, and whether any cell replacements may be necessary:

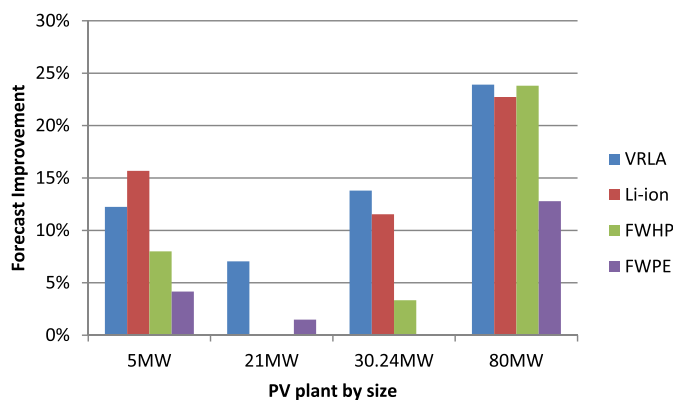


Fig. 9. Percentage violation reduction improvement of having a perfect forecast for the remainder of the 1 min averaging period compared to the extrapolation of recent power output. The ESU sizes were kept the same as for the 99% violation reduction seen in Fig. 8.

For FWPE: $22,000 \text{ kW} * \$2159/\text{kW} = \47.5M ; similarly for Li-ion: $\$32.5\text{M}$, and for VRLA: $\$37.3\text{M}$

The number of equivalent full cycles per year for FWPE, Li-ion and VRLA are relatively low – respectively 477, 16 and 26 – and given the cycle life of the batteries we can expect that cycle life will not be the limiting factor for any necessary replacements, although calendar life potentially could have an impact. If we assume no cell replacements are necessary, we can compare fixed and variable O&M as follows:

$$\begin{aligned} \text{FWPE: } & \$5.8/\text{kW/yr} * 22,000 + 477 * 5500 \text{ kWh} * 2 * 0.0003 = \$127,600/\text{yr} + \$1574/\text{yr} = \sim \$129,000/\text{yr} \\ \text{Li-ion: } & \$8.3/\text{kW/yr} * 22,000 + 16 * 11,000 \text{ kWh} * 2 * 0.0110 = \$182,600/\text{yr} + \$3872/\text{yr} = \sim \$186,500/\text{yr} \\ \text{VRLA: } & \$9.2/\text{kW/yr} * 22,000 + 26 * 11,000 \text{ kWh} * 2 * 0.0008 = \$202,400/\text{yr} + \$458/\text{yr} = \sim \$202,900/\text{yr} \end{aligned}$$

According to this simple analysis, Li-ion batteries are the most economic option for the considered case as it has a definite capex advantage, as well as an O&M advantage over VRLA batteries. The O&M cost of FWPE is lower than that of the batteries but its capex is much higher.

A more complete economic analysis would be the topic of future work.

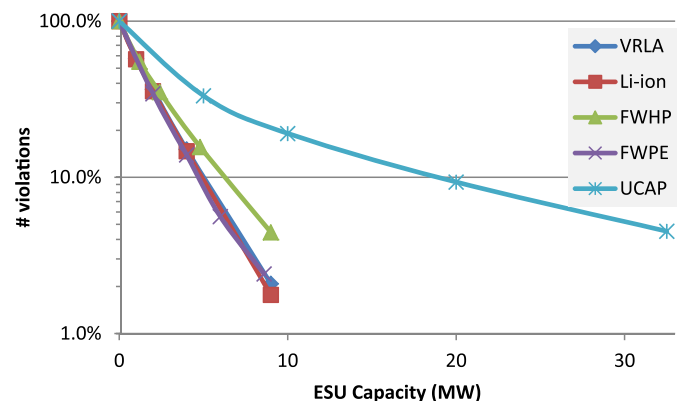


Fig. 10. Normalized number of 5%/minute violations as a function of the ESU power capacity in MW (100% = 4977 violations). The graph reflects how the stricter ramping limit demands a higher energy capacity from the ESU, as the Flywheel High Power (P:E ratio = 12:1) has moved away from the cluster of lower P:E ratio technologies compared to Fig. 7.

Table 3

Number of full cycles performed by the Energy Storage Unit over a full year at each plant. The ESU is sized to reduce 99.0% of violations.

Full cycles	VRLA	Li-ion	FWHP	FWPE	UCAP
Cycle life	700	1000	100,000	100,000	1,000,000
5 MW	61	50	766	494	861
21 MW	37	27	586	443	614
30.24 MW	55	44	735	519	783
80 MW	26	16	589	477	606

5. Conclusions

Many studies have shown how large numbers of small PV systems together yield reduced power output variability, analogous to loads on the grid. However, grid balancing authorities are concerned about large-scale PV variability and have initiated regulations to limit ramp rates of individual plants to avoid potential frequency regulation issues on their grid. In this study, we developed a model to simulate effective dispatch of Energy Storage Units to provide ramp rate control for individual plants. With second-by-second power output time series obtained from four multi-MW PV plants, we simulated ramp rate control performance for five storage technologies and a range of storage sizes. We developed two dispatch strategies, tailored to high and low cycle life technologies. Overall, we find that the model developed can be useful in finding the appropriate size ESU for a certain performance requirement (i.e. mitigation of ramp limit violations). This can then be used in determining the added cost of ESU ramp rate support.

We found individual PV plant ramp rate control to be a 'power application', thus the Energy Storage Unit benefits from a relatively high power capacity. For Power:Energy ratios up to 12:1 (discharge time >5 min) we found that the ESU size needed to overcome 10%/minute ramping violations is dependent on its power capacity, not energy capacity. For all plants studied in this paper, the violation reduction performance closely follows an exponential decay function with increasing power capacity. For ultra-capacitors with a P:E ratio of 50:1 we saw energy-limited ramp rate control, therefore the need to scale up the ESU to satisfy the necessary energy capacity, which amounts to 1.7, 1.9, 1.7 and 1.2 min of storage for the 5, 21, 30.24 and 80 MW plants, respectively. Because the FWHP (High Power Flywheel) system on

the left side of Fig. 8 is close to these ultra-capacitor energy capacities, we believe that its accompanying P:E ratio of 12:1 is close to the optimum P:E ratio to overcome 10%/minute violations for the plants studied here. For an even stricter ramping limit of 5%/minute, we see a shift to a lower P:E ratio, as the necessary ESU energy capacity increases compared to the maximum power output.

For the ESUs sized to mitigate 99% of violations, we found an additional violation reduction of up to 24% when perfect forecasting was assumed for the remainder of the averaging period. Since forecasting allows the dispatch model to more evenly spread out power production over the averaging period, we expect that forecasting will be even more beneficial for smaller ESU systems that often yield violations due to power limitations, but this is one of the topics of further research as described below.

6. Further research needs

This study investigated the operation of ESUs under a 10%/minute ramping limit for the specific plants and their respective locations and climate contexts. Therefore, further research is needed to test the algorithm on a wider variety of PV plants in different geographic regions.

The wide variety of user input parameters in the model allow for an extensive sensitivity analysis to study the impact of parameters on results. For example, a range of Power-to-Energy ratios can be simulated for a single ESU technology to find the optimum ratio for violation reduction. Also, more Energy Storage technologies (e.g. battery chemistries) can be simulated and their operational performance compared. In addition, we intend to investigate the benefit of using two ESU technologies in parallel (e.g. ultra-capacitors and batteries) for ramp rate control.

An important consideration for plants operating under ramping limits is the added cost of the ESU. The benefits of the ramp rate support from the ESU need to offset the capital and operating costs. As shown in the previous section, cost analyses can be based on the minimum required capacity for satisfying a given level of ramp-rate control for each of the considered ESUs. Recent investments on battery research, development and deployment create the potential for drastic cost reductions; thus technology and life-expectancy improvements would be included in prospective cost analyses.

Table 4

Losses associated with the operation of ESUs to achieve 99% reduction of ramping violations, expressed in percent of annual energy production. L_s stands for self-discharge losses and L_t is 'transfer losses' related to charge and discharge efficiencies.

Losses [% of AEP]	VRLA		Li-ion		FWHP		FWPE		UCAP	
	L_s	L_t	L_s	L_t	L_s	L_t	L_s	L_t	L_s	L_t
5 MW	0.168%	0.020%	0.024%	0.046%	0.353%	0.249%	1.006%	0.472%	0.056%	0.151%
21 MW	0.112%	0.009%	0.016%	0.016%	0.348%	0.135%	0.994%	0.298%	0.061%	0.082%
30.24 MW	0.110%	0.007%	0.016%	0.026%	0.324%	0.162%	0.943%	0.341%	0.056%	0.099%
80 MW	0.109%	0.003%	0.016%	0.009%	0.221%	0.122%	0.660%	0.300%	0.040%	0.077%

Table 5

Energy storage unit costs.

Technology	Flywheel [17] (15 min)	Li-ion battery [19]	VRLA battery [19]
Total plant cost	\$2159/kW, \$8636/kWh	\$1475/kW, \$2949/kWh	\$1695/kW, \$3391/kWh
Maintenance Costs	\$5.8/kW/yr,	\$8.3/kW/yr,	\$9.2/kW/yr, \$0.0008/kWh
Fixed/Variable ^a	\$0.0003/kWh	\$0.0110/kWh	
Cycle life	100,000	1900 @80% DoD [18]	~700 @80% DoD [18,19]

^a Variable O&M is for both charging and discharging.

The economic benefits would depend on electricity market pricing and ramping rate violation fees.

References

- [1] PREPA. Minimum technical requirements for interconnection of photovoltaic (PV) facilities. Puerto Rico Electric Power Authority; 2011. p. 1–7.
- [2] CAISO. Flexible ramping product. 2011 [Online]. Available: <http://bit.ly/164LbhU>.
- [3] Wiemken E, Beyer HG, Heydenreich W, Kiefer K. Power characteristics of PV ensembles: experiences from the combined power production of 100 grid connected PV systems distributed over the area of Germany. *Sol Energy* 2001;70(6):513–8.
- [4] Murata A, Yamaguchi H, Otani K. A method of estimating the output fluctuation of many photovoltaic power generation systems dispersed in a wide area. *Electr Eng Jpn* Mar. 2009;166(4):9–19.
- [5] Mills A, Ahlstrom M, Brower M, Ellis A, George R, Hoff T, et al. Dark shadows. *IEEE Power Energy Mag* June. 2011;33–41.
- [6] Hansen T. Utility solar generation valuation methods. Jun. 2007. Tucson, AZ.
- [7] Kankiewicz A, Sengupta M, Moon D. Observed impacts of transient clouds on utility-scale PV fields. In: *Solar 2010 Conference Proceedings*, 2010, vol. 2009; December 2009.
- [8] Hoff TE, Perez R. Quantifying PV power output variability. *Sol Energy* Oct. 2010;84(10):1782–93.
- [9] Lave M, Kleissl J, Stein J. Quantifying and simulating solar-plant variability using irradiance data. Elsevier; 2013. p. 149–69.
- [10] Lave M, Kleissl J, Stein JS. A wavelet-based variability model (WVM) for solar PV power plants. *IEEE Trans Sustain Energy* Apr. 2013;4(2):501–9.
- [11] Lenox C. Variability in a large-scale PV installation. In: *Utility-scale PV Variability Workshop*; 2009.
- [12] Haaren R, Morjaria M, Fthenakis V. Empirical assessment of short-term variability from utility-scale solar PV plants. *Prog Photovoltaics Res Appl* 2014;22(5):548–59.
- [13] Perez R, Hoff T, Dise S, Chlamers D, Kivalov S. Mitigating short-term PV output intermittency. In: *29th European PV Solar Energy Conference*, Amsterdam; 2014.
- [14] Fthenakis VM, Nikolakakis T. Storage needs and options for solar renewable energy. *Compr Renew Energy* 2012;1:199–211.
- [15] Manz BD, Piwko R, Miller N. Look before you leap. *IEEE Power Energy Mag* August. 2012;75–84.
- [16] Greening B, Azapagic A. Environmental impacts of micro-wind turbines and their potential to contribute to UK climate change targets. *Energy* Sep. 2013;59:454–66.
- [17] Beacon Power, Flywheel spec sheet, [Online]. Available: www.beaconpower.com/files/FESS_Tech_Data_Sheet.pdf.
- [18] Albright G. A comparison of lead acid to lithium-ion in stationary storage applications. March, 2012.
- [19] Akhil A, Huff G, Currier A, Kaun B. DOE/EPRI 2013 electricity storage handbook in collaboration with NRECA. 2013. Albuquerque, NM.
- [20] Pena-Alzola R, Sebastian R, Quesada J, Colmenar A. Review of flywheel based energy storage systems. In: *Proceedings of the 2011 International Conference on Power Engineering, Energy and Electrical Drives*; May. 2011.
- [21] Bindner H, Cronin T, Lundsager P, Manwell JF, Abdulwahid U, Baring-gould I. Lifetime modelling of lead acid batteries. 2005. Roskilde, Denmark.
- [22] Maxwell Technologies, 160V module product specifications. [Online]. Available: http://www.maxwell.com/products/ultracapacitors/docs/maxwell_160v_datasheet_v4.pdf.
- [23] Mallika S, Kumar RS. Review on ultracapacitor-battery interface for energy management system. *Int J Eng Technol* 2011;3(1):37–43.
- [24] Lave M, Kleissl J, Ellis A, Mejia F. Simulated PV power plant variability: impact of utility-imposed ramp limitations in puerto rico. 2013. p. 2–6.
- [25] Lave M, Kleissl J. Testing a wavelet-based variability model (WVM) for solar PV power plants. In: *Power and Energy Society*; 2011. p. 1–6.