An Analysis of Storage Requirements and Benefits of Short-Term Forecasting for PV Ramp Rate Mitigation

Daniel Fregosi, Nicholas Pilot, Michael Bolen, and William B. Hobbs

Abstract—**As renewable energy penetration on the grid increases, requirements are being placed on PV owners and operators to limit power ramp rates. PV power ramping is an issue for grid stability because generation load balance must be continually met. When a large PV resource significantly increases or decreases, another resource must compensate. To aid in grid stability, ramp rate limitations have been imposed on PV plants. This article addresses how much fast-responding storage is needed to mitigate high ramp rates of PV plants, and how much benefit is there from short-term power forecasting in terms of reducing the storage requirement. The results provide a baseline estimate for system planners and designers. Furthermore, the storage controller design and optimization are given, along with the open-source code, such that others can tailor the simulation to their specific plant and weather profile. Results from studying a 100 MW PV plant power production profile show a reduction in ramp-rate violations from 10% of yearly intervals to below 1% with 12 min of storage. With forecasting, the same level of smoothing is achieved with a 5-min rated storage. A sensitivity analysis shows the impacts of varying constraints, such as storage power rating, PV system size for geographic smoothing, forecast window length, and the ramp-rate limit magnitude.**

Index Terms—**Battery, forecasting, PV, ramp rate, smoothing, storage.**

I. Introduction

PV POWER ramping is an issue for grid stability since generation-load balance must always be met, and when a large PV resource significantly increases or decreases, another resource must compensate to ensure matching. Traditional dispatchable resources have a limited ability to respond quickly. Ramping of PV output due to transient cloud cover has been an issue discussed within the solar industry for over 35 years. PV ramping has been shown to cause significant power quality issues and voltage fluctuations and is dependent on the size of the PV system [1], [2], [3], [4], [5]. Increased ramp rate frequency, due to growing PV penetration, has led to the adoption of ramp rate limitations imposed by utilities in Germany, Ireland, Denmark, Puerto Rico, Hawaii, and elsewhere [6], [7]. In Puerto Rico (Puerto Rico Electric Power Authority) and Germany, ramp rate limitations are set at 10% per minute of the rated PV output power, whereas in Ireland (EirGrid), Hawaii (Hawaiian Electric Company) and Denmark (Energinet), the ramp rate is specifically limited to 30 MW per minute, $\pm$2MW per minute and 100 kW per second, respectively [6], [7], [8].

To alleviate grid impacts, research such as Sangwongwanich et al. [9] shows opportunities to cost-effectively curtail at the PV inverter level. However, this curtailment is limited to mitigating only up-ramps caused by an increase in PV plant output and is unable to reduce down-ramps. Battery energy storage systems (BESSs), such as lithium-ion batteries, are a suitable candidate to alleviate both up-ramps and down-ramps as they are able to rapidly add or subtract power to smooth PV plant output, mitigating ramp rates [10]. Sukumar et al. [11] highlights the pros and cons of various PV ramp rate smoothing methodologies that exist in the literature, such as moving averages and exponential smoothing based methods, filter-based techniques, and ramp rate control algorithms [4], [12], [13], [14], [15], [16], [17] and summarizes that ramp-rate based control algorithms are advantageous over the other types, despite moving average and filter-based techniques being more predominant in literature. Ramp-rate control algorithms have the flexibility for designers to incorporate strategic charge and discharge rules based on physical or historical knowledge of the application. The ramp rate controller presented here follows intuitive control objectives and is flexible enough to work with or without short-term forecasting.

Several ramp-rate control algorithms found in literature provide a basis for the design of the controller presented here. Marcos et al. [14] employ a ramp-rate based control algorithm to calculate the minimum energy storage requirements through validation with recorded data from three PV plants, proposing a model utilizing power exponential decay. Additional related work was done by Huo and Gruosso [18] in developing a ramp rate control strategy for microgrid PV + BESS systems. Lam and Yeh [16] analyzes PV ramp rate control along with reducing battery cost and energy requirements.

However, these controllers are based only on instantaneous power data and do not incorporate short-term forecasting. Research by Ryu et al. [19] incorporated a "predictive tracking" ramp rate strategy using short-term forecasting with an SOC feedback strategy, relying on a neural network-based forecast

Manuscript received 29 July 2022; revised 28 October 2022; accepted 31 October 2022. Date of publication 9 January 2023; date of current version 20 February 2023. The work was supported by EPRI and Southern Company. *(Corresponding author: Daniel Fregosi.)*

Daniel Fregosi, Nicholas Pilot, and Michael Bolen are with the Electric Power Research Institute, Palo Alto, CA 94304 USA (e-mail: dfregosi@epri.com; npilot@epri.com; mbolen@epri.com).

William B. Hobbs is with the Southern Company, Birmingham, AL 35203 USA (e-mail: whobbs@southernco.com).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/JPHOTOV.2022.3231713.

Digital Object Identifier 10.1109/JPHOTOV.2022.3231713

model consisting of historical solar irradiance measurements and total-sky images.

This article seeks to fill a research gap by specifically focusing on the storage sizing requirements necessary for ramp rate smoothing. Studies focusing on the storage requirement for ramp rate control are limited. The controller presented here extends upon ones in the literature to incorporate short-term forecasting. Furthermore, the controller is practical to implement and intuitive since it is based on the well-used proportional-integral-derivative controller. In this article, the controller is applied to a system with realistic storage and grid constraints. By focusing on the storage requirements, this article helps PV, storage, and grid system designers to better plan and optimize their designs. Variations on the system design and specific grid constraints are considered to assess the impact on PV smoothing from the system design perspective.

The objective of the energy storage in this article is to provide smoothing, rather than firming. In smoothing, storage limits the rate of change of power in order to buy time for the larger power system to respond. In firming applications, the objective is to hold the power steady to a predefined value for specific periods of time, e.g., 30 min to an hour. Firming is a more storage intensive objective than smoothing. For smoothing applications, short-term power forecasting on the order of 15 to 30 min can make an impact on the storage requirement by allowing the controller to anticipate and prepare for ramping events. In firming applications, longer-term forecasting, on the order of hours to a day, plays a significant role.

Short term PV power forecasts can be made by examining cloud position and velocity and anticipating the shading impact. Forecasts can be relatively accurate for periods under an hour. The work by Kumler et al. [20] shows a decrease of nearly 50% in mean absolute error for a 5-min forecast compared to a 30-min forecast using a physics-based smart persistence model for intrahour solar forecasting (PSPI). Additionally, Chen et al. [21]. utilizing a dynamic spatial-temporal ramp algorithm as a solution for power ramp rate control based on ground-based sensor forecasting systems shows an annual normalized mean absolute error of 6.2% for short-term forecasting, with an average accuracy rate of 95%.

The two main objectives of this article are to study the storage requirements for PV smoothing and to provide a controller to be used by planners and designers to simulate specific systems with specific constraints and weather patterns. The code is posted publicly [22] and the controller is fully documented here. In addition, the controller has been incorporated into system advisor model (SAM) in version December 2, 2021. The publicly available algorithm fills an industry gap by helping system planners and designers estimate storage requirements. In practice, the controllers designed and used by commercial storage providers are proprietary, thus inaccessible to the planners and designers.

II. Problem Setup

The primary question addressed in this article is: how much storage is needed (in terms of both energy and power) to smooth PV production and how much does forecasting reduce the storage requirement? In this article, a series of simulations are performed using power production data from a large-scale PV plant and a simulated energy storage system and controller. In the simulations, the controller utilizes the storage system to smooth the PV power, subject to the system constraints, which are described next. When the storage system is unable to limit the PV power to stay within the ramp rate limitation, a violation occurs. The total number of violations over the simulation period is the metric of storage effectiveness.

TABLE I
Problem Setup—Base Case and Sensitivities

Parameter	Base	Sensitivity Variation(s)
Storage Energy Capacity	0.1 hours (6 min)	Sweep 0.3 hr. (18 min.) to 0.025 hr. (1.5 min.)
Storage Power Capacity	100% of PV AC Capacity	75%, 50%, 25%, 15%, 10%
Ramp Rate Limit	10% of AC capacity per interval	7.5%, 5%, 2.5%
Forecasting Length	None, 30 min	10, 20, 40 minutes
PV Size (geographic smoothing)	Full plant (100MW)	40 MW, 4 MW, 1 MW
Curtail to limit up-ramping	No	Yes
System Power Constraint	0 ≤ PV+Storage Power ≤ Nameplate AC * 1.05	Allow grid charge

Ramp rates are defined in terms of the change in power from one interval to the next as a percentage of the plant's ac capacity. Ramp rates are given in relative terms rather than absolute to make the results more generalizable. For absolute ramp rate limits, the rating of the PV plant is the dominant factor impacting the storage requirement. In this article, an interval spans 10 min, although a range of intervals could be considered based on the local restrictions (e.g., 1 min or 15 min). The ramp rate is calculated based on the discrete average of each interval, rather than a rolling average as is predominantly performed in the literature [4]. Constraints that limit the storage device's ability to smooth are its energy capacity and power capacity. Energy capacity is given in terms of duration in hours at the ac rating of the PV plant. For example, a 50 MWh storage at a 100 MW PV plant has an energy capacity of 0.5 h. Power capacity is given as a percentage of the capacity of the PV plant.

In designing the scenarios to analyze, a base-case is considered initially to represent a typical configuration. Next, variations on each of the configuration parameters are considered one at a time to understand their specific impacts on the storage requirement. Table I gives the configuration parameters for both the base case and the sensitivity analysis. In the base case, the storage power capacity is equal to the PV system ac capacity. In the sensitivity analysis, the power capacity is reduced to assess the impact on smoothing. Beyond the constraints of the storage system, there are a few additional system constraints that are typical for PV plus storage applications and are imposed by the grid owner, described next. First, the combined PV plus storage power cannot exceed the PV ac capacity, with a 5% margin. Second, the PV plus storage system cannot draw power from the grid. Finally, in the base case, PV power curtailment is not considered as an option to limit up-ramps. While curtailment is

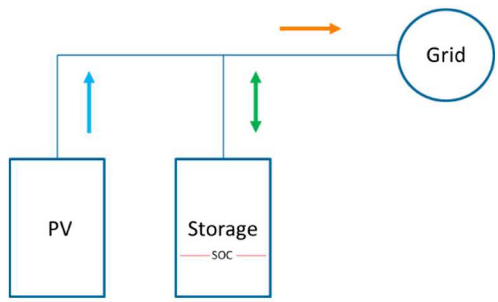

Fig. 1. AC coupled PV plus storage system block diagram.

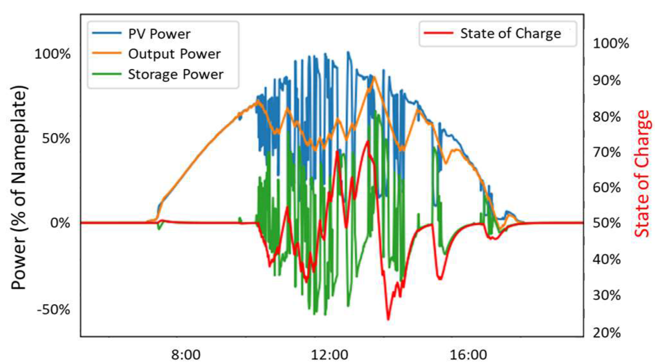

Fig. 2. Example PV power and smoothing profile for a highly variable day.

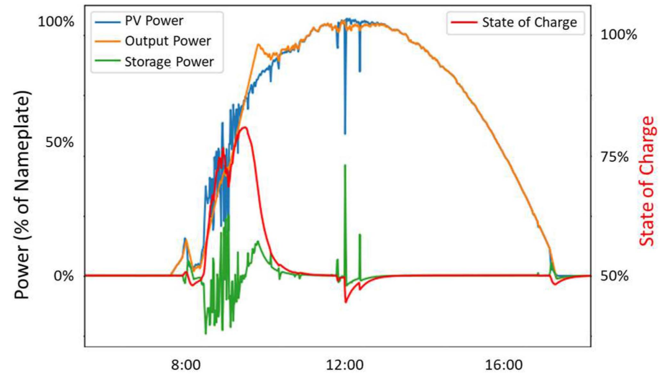

Fig. 3. Example of state-of-charge recovery by output power overshoot.

an effective technique to limit up-ramps [9] by simply dumping excess energy, the owner loses revenue due to the lost energy. An economic analysis specific to the conditions of a particular system would inform whether the curtailment is a viable method. For this reason, curtailing up-ramps is studied as a variation on the base case.

The storage system is ac coupled with the PV system and a round trip efficiency of 90% is applied to account for losses in the storage system, including power electronics. In the SAM release, the detailed technology-specific battery model is used to calculate round trip efficiency losses. Storage dynamics and response times are considered instantaneous from the perspective of this article since intervals of smoothing are on the order of minutes and batteries and power electronics are able to respond on the order of seconds.

III. Controller Design

In designing a storage controller, the goal is to provide an effective yet straightforward controller to use in simulation to estimate the storage requirements. This design provides a baseline to which the performance of other controllers can be compared. The controller inputs are the unsmoothed PV system power (averaged over the ramp interval) and the storage state of charge (SOC). Additionally, with the forecast option, the controller has an estimate of future PV power up to 30 min ahead.

A proportional plus integral feedback controller is utilized to find the desired system output power (PV plus storage), pictured in orange in Fig. 1 through Fig. 3. The storage power is then controlled based on the difference between desired system power and PV power. The feedback controller compares the system output power to the reference PV power to compute the error term. After calculating the error, the proportional and integral control terms are utilized to track the PV power and return the storage to the resting SOC, respectively. The output power is subject to the ramp rate limitation, so output power will not perfectly track PV power. Differences in PV power and output power are compensated with storage, and result in changes to the storage SOC. As illustrated Fig. 2, the output power will track roughly in the middle of the PV power during variable times in which the PV power ramps exceed the ramp rate limit. In successfully tracking the PV power, the controller minimizes the amount of power sent into or out of the storage. In returning the storage back to a nominal SOC, the controller avoids unnecessarily operating at near empty or near full, such that it is ready to respond to future ramps in either direction.

The SOC deviates from the resting SOC of 50% throughout the day. The secondary Y-axis shows the magnitude of variations. The profile in Fig. 3 illustrates the influence of the integrator term. In this PV profile, smoothing in the morning causes the SOC to rise to over 75%. After the PV returns to a smooth profile and the output power catches up to the PV power, the controller seeks to return the SOC to the resting value by overshooting the PV power for a short period to discharge the storage. To balance the proportional and integral terms, an optimization is performed on a set of training data from the plant. The optimizer is described in a later section.

Short-term PV power forecasting can improve the performance of a smoothing controller. If ramping events can be anticipated, the controller can smooth the output before PV power changes by beginning to ramp the output power in the same direction as the anticipated PV power ramp. This is demonstrated in Fig. 4. On the bottom, without forecasting, storage begins discharging at the point when PV begins to drop. The energy expended by storage to slow down the power drop is proportional to the shaded area, and the maximum power required by the storage is proportional to the vertical line. On the top, with forecasting, the controller can begin reducing total system output power by proactively pre-charging the storage before the PV power drops. Once the PV power drops and crosses over the

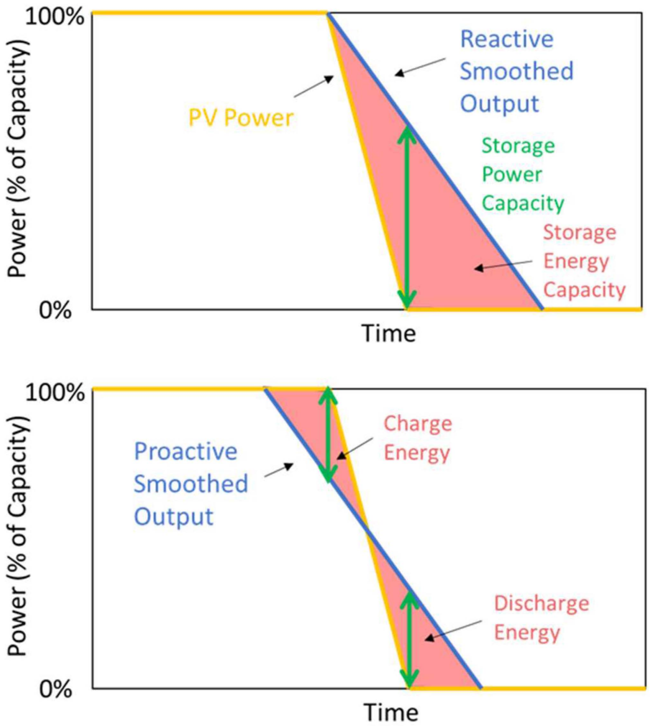

Fig. 4. Example showing storage energy and power utilization without forecasting (top) and with forecasting (bottom).

output power, the controller switches to discharging the storage to maintain the desired output power slope. At the end of the ramping event, the SOC is roughly the same as it was before since the storage both charged and discharged. The energy capacity requirement is proportional to one of the shaded triangles, and the power requirement is proportional to one of the vertical lines, whichever is larger. In this illustration, forecasting allows the power capacity requirement to be reduced by about 50%, and the energy requirement to be reduced by about 75%.

Forecasting is incorporated into the controller by adding a forecasting term in addition to the proportional and integral terms. The forecasting term is another integral term, as it is proportional to the energy difference between the current output trajectory and the power forecast. The controller implementation is described in more detail in the next section.

The four parameters in the controller (proportional, integral, forecast, and resting SOC) are system and location specific for optimal performance. A binary-search parameter optimization algorithm was implemented to find the best parameters for each simulation condition. The parameter optimization algorithm is included along with the full controller in the public repository and described in more detail next.

IV. Controller Implementation and Optimization

The controller structure is illustrated in the block diagram in Fig. 5. The controller has three control constants, K_p (proportional), K_i (integral), and K_f (forecast) and one reference setting, SOC_0 (resting SOC), pictured in orange. The three control constants set the relative influence of the three control objectives.

The proportional term acts upon the error between the reference PV power and previous output power. The proportional control constant, K_p, sets how aggressively the output power tracks PV power. If it is set larger than one, the output power will jump ahead of the PV power. Tracking too aggressively will lead to unnecessary cycling of the storage, whereas tracking too weakly will lead to large errors causing major deviations in the storage SOC.

The integral term acts upon error between the resting SOC and the actual SOC. The integral control constant K_i sets how aggressively the storage returns to the resting SOC. It is generally weaker than the proportional term, as the storage can return to the resting SOC over time.

The forecast term sets how aggressively the system responds to future ramps. Figs. 6 and 7 illustrate how the forecast controller works. At time T_0, the output power is represented by the red dot and the output trajectory is found by extending the output power into the future. If a PV power forecast is available, it is compared against the output trajectory, and the area between the curves is calculated as the forecast storage energy accumulation. This is the energy accumulation that would occur if no changes were made to the output trajectory. Now that the storage energy accumulation is anticipated, the controller may begin to ramp output power in the direction of the anticipated PV power ramp, as in Fig. 7.

The three control terms are summed to find the desired power increment. A series of constraints are then applied to ensure the system is staying within its operation boundaries. First, the max step constraint limits the size of the power increment, or decrement if negative, that the output power can take from one interval to the next. This is done to enforce the maximum ramp rate of output power. The ramp-rate constrained power increment is added to the previous output power before the storage power and energy limitations are applied. The power limits ensure that output power does not exceed the ac capacity of the system, output power is not negative such that power is drawn from the grid, and storage power does not exceed its power rating (for the cases where storage power capacity is less than PV system nameplate). The SOC limits simply prevent charging storage after it is full and discharging after it is empty.

The controller performance depends on finding the optimal balance of the four controller parameters (K_p, K_i, K_f, and SOC_0). Furthermore, the optimal values are different for each specific system. Variations that impact the control parameters include storage size, PV system design, and weather and climate. To address this challenge, an optimizer was designed to find the control parameters that minimize the ramp rate violations for a given system specification and power profile.

The optimizer first splits the PV power data into training and testing datasets. In this case, the full dataset contains one year of power data. Half of the complete days were randomly selected out of the full dataset to be part of the training dataset and the remainder are used as the testing dataset. The optimized parameters are tested on a different dataset than the one used for

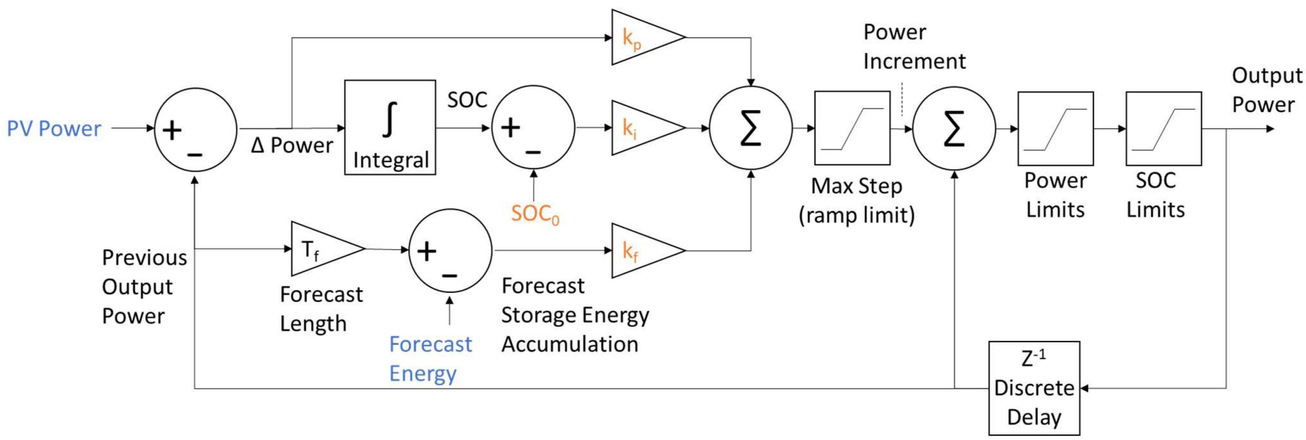

Fig. 5. Ramp rate smoothing controller block diagram.

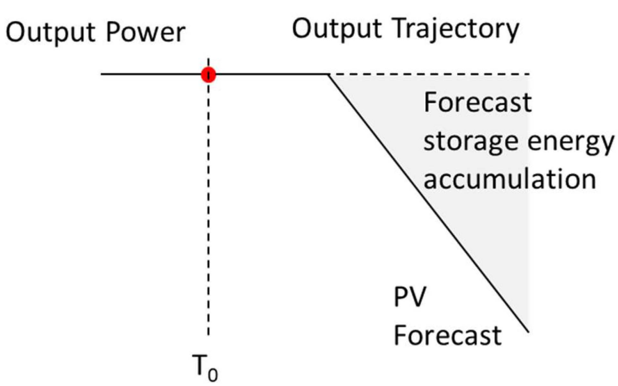

Fig. 6. Illustration of forecast storage energy accumulation.

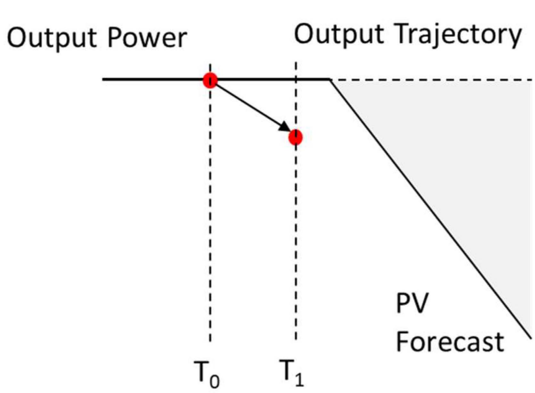

Fig. 7. Controller response to forecast storage energy accumulation.

training to avoid overfitting the controller parameters to specific days in the training dataset.

The optimizer works by searching and narrowing the parameter space in successive iterations until the controller performance no longer improves. In each optimizer iteration, the parameter space is divided into halves for each control parameter. For four control parameters, the parameter space is divided into 16 independent sections. The top performing set of parameters are selected among the 16 sets. Thus, the parameter space is reduced by 1/16 each optimizer iteration. This straightforward, binomial search optimizer reaches a solution relatively quickly compared to other optimizers. A potential weakness is that it may be susceptible to finding a local minimum when the solution space is non-convex. As an alternative, evolutionary algorithms are well suited for non-convex optimization functions, while their convergence speed is slower. An example use of particle swarm and genetic algorithm optimizers has been demonstrated using SAM [23], although not for this particular application. In this example by Pilot et al., the python-based version of SAM is utilized to integrate the model with the optimizer. A similar approach could be taken by users to optimize the ramp rate smoothing controller parameters once it is incorporated into SAM.

V. Results

In the following analyses, performance data was used from a 100 MW PV plant in the Southeast US. The data spans one year and is recorded at 1-min averaged intervals. While these results are specific to this PV system, weather pattern, and grid requirements, others can perform the analysis on their own systems, locations, and grid requirements in SAM or using the publicly available code [22].

A. *Benefits of Short-Term PV Forecasting*

The initial analysis explores the storage requirement for the base PV plus storage scenario, as given in Table I. In addition, the benefits of using short-term PV power forecasting are analyzed by comparing the results against the base, nonforecasting case. The base case considers a 10% per 10-min interval ramp rate limit, and the storage power capacity is equal to the PV system power capacity.

Short-term PV power forecasts are not 100% accurate in practice. Since PV forecasting is a developing field of study and is outside the scope of this article, the impacts of less-than-perfect accuracy are not studied here. Therefore, the PV power forecast used in this article is a perfect forecast, found by looking ahead at the PV power production 30 min in the future (3 ramp rate interval time-steps). This approach puts an upper-bound on the benefits of short-term forecasting, since practical forecasts will

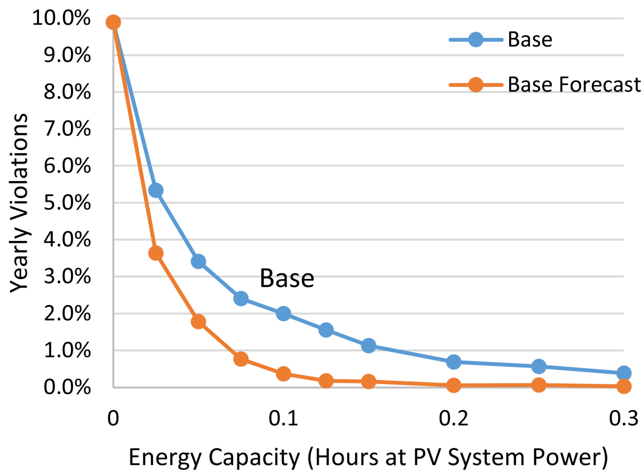

Fig. 8. Ramp rate violations as a function of storage energy capacity.

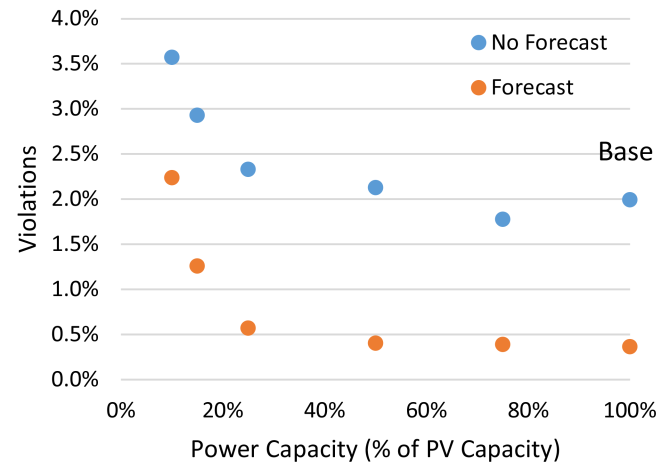

Fig. 9. Effects of varying storage power capacity (0.1 h energy rating).

be less accurate. In the SAM implementation of the controller, the option is given to the user whether to use a perfect look-ahead forecast or to input a custom forecast that is less-than-perfect. With this option, designers can study the impact of different quality forecasts.

Fig. 8 shows the yearly violations for the *base* controller and the *base forecast* controller as storage energy capacity varies. Yearly ramp-rate violations are the metric used to measure the effectiveness of the storage plus controller system. Grid operators will likely specify a small number of violations to be permitted, since it is not economical to eliminate 100% of violations and the system can accommodate a small percentage. Yearly violations are presented as a percentage of the total intervals for the year. Without any storage (zero energy capacity on the chart), the PV power violates the ramp rate requirement on 10% of the 10-min intervals for the year at this PV plant. As the storage energy capacity increases, the yearly violations decrease. An optimization was performed to find the controller parameters for each point on the graph. The results are not completely smooth, as some randomness is involved in the optimizer. However, the random variations are not large enough to obscure the underlying trends.

In both controllers, the ramp rate violations are significantly reduced with only a few minutes of storage, and all but eliminated with 0.3 h (18 min) of storage. The controller with short-term forecasting demonstrated significantly improved performance over the nonforecasting controller. With 0.1 h (6 min) of storage energy capacity, the nonforecasting-controlled system has 2% yearly violations, while the forecasting-controlled system has 0.4% yearly violations. Without forecasting, violations cross below 1% with 0.2 h (12 min) of storage, whereas with forecasting violations cross below 1% with only 0.075 h (4.5 min) of storage. Violations are virtually eliminated at 0.1% with 0.2 h (12 min) of energy capacity in the forecasting controller.

Overall, the results indicate that the storage capacity required to mitigate ramp rates is relatively low, on the order of 10 min. This is much lower than other storage applications, like firming or peak shifting, which typically require several hours of storage. Furthermore, with the addition of short-term forecasting, the performance significantly improves, thus further reducing the storage energy capacity required for smoothing.

B. Impact of Varying Power Capacity

Next, the effects of varying the energy storage power capacity are analyzed. The power capacity, or maximum instantaneous power, is a significant consideration as it impacts the cost of the system. System components, such as power electronics, electrical balance of systems, and even the battery cell, are all impacted by the power capacity rating and must be sized accordingly. In the base case, the storage power capacity is equal to the PV system capacity. Fig. 9 shows the effects of reducing the storage power rating from 100%, in the base case, down to 10%. The results are shown for both the forecast and non-forecast controllers. In these simulations where the power capacity is varying, the battery energy capacity is set to 0.1 h (6 min).

Interestingly, the performance impact is minimal until the power capacity drops below 20% of the PV system capacity. The trends are very similar for both the forecast and non-forecast case. These results suggest that the storage power capacity can be significantly lower than the PV system capacity without losing the ability to smooth ramp rates. This result is significant for achieving cost reductions or for using a storage system for multiple storage objectives. For example, a storage system that is primarily used for peak shifting could allocate a small fraction of its energy and power capacity for power smoothing.

These results can be understood by examining the distribution of ramp rate magnitudes in the unsmoothed PV power dataset. Fig. 10 shows the count and cumulative distribution of ramp rates, calculated at 10-min intervals and represented as a percentage of PV capacity. A 20% or larger ramp rate occurs in only 3.5% of the intervals. One notable result is that the controller with forecasting is able to achieve very low violation counts even with the reduced power capacity. While 3.5% of ramp rates are above 20%, total violations are limited to less than 1% of the PV output. This illustrates the value of proactively charging and

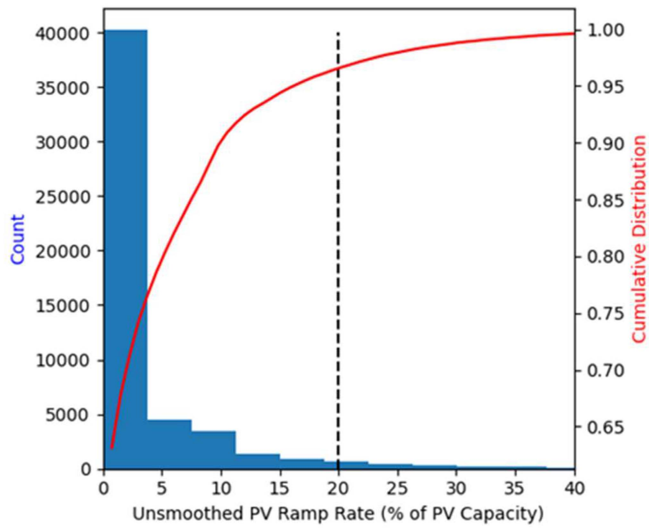

Fig. 10. Distribution of unsmoothed PV ramp rates.

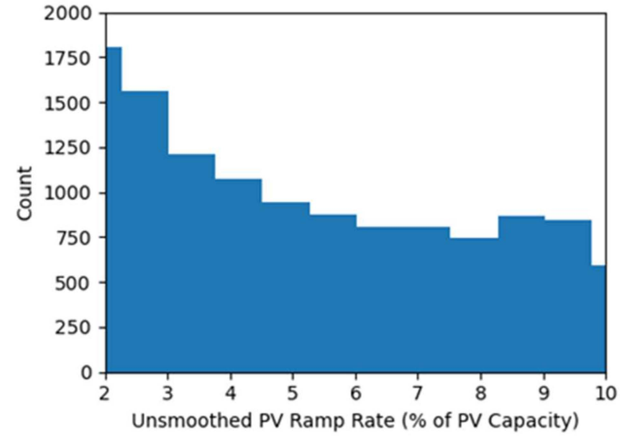

Fig. 12. Distribution of unsmoothed PV ramp rates from 2% to 10% of PV capacity per interval.

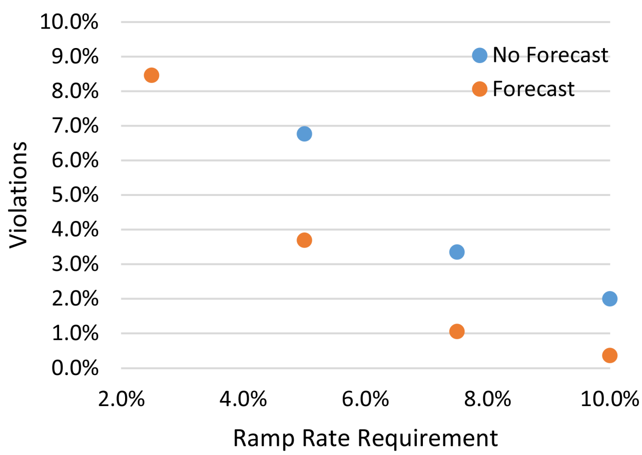

Fig. 11. Effects of varying ramp rate slope limit (0.1 h energy rating).

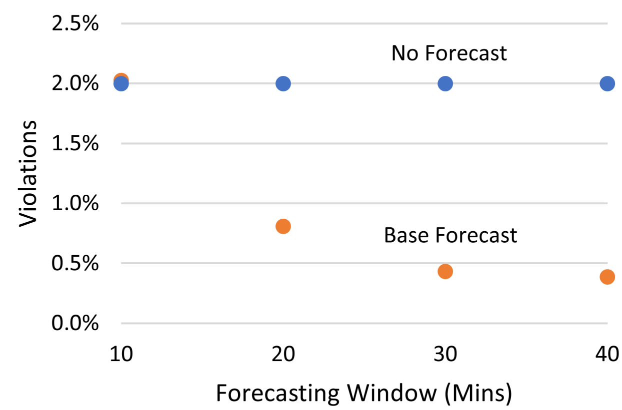

Fig. 13. Effects of varying forecast window length.

discharging in anticipation of ramp events to reduce the burden on the storage.

C. Impact of Varying Ramp Rate Requirement

Next, the effects of constraining the maximum allowable ramp rate requirement were studied. This sensitivity informs both plant operators and grid operators on the impacts of changing the ramp rate requirement and the capability of the storage system to meet or exceed stricter hypothetical requirements. The system was simulated for ramp rate limits from 10% per interval in the base case down to 2%. Fig. 11 shows that violations increase nearly linearly as the maximum allowable ramp rate requirement reduces or becomes stricter. A closer look at the distribution of unsmoothed PV ramp rates in this range, given in Fig. 12, reveals relatively flat distribution with an increase at the very low range. This is consistent with a nearly linear increase in the violation count as the requirement tightens.

D. Impact of Varying Forecast Window

As forecasting methods and products are being developed and evaluated, it is useful to examine the impact of the forecasting window length. By studying the effects of varying the forecast window length, operators may better evaluate forecasting devices, which may offer different forecast lengths at different prices or levels of accuracy. For example, a reduction in accuracy of nearly 50% was observed when moving from a 5-min to a 30-min forecast in [20]. The negative impacts of a shorter window are explored here.

The base forecasting controller demonstrated the value of 30-min ahead forecasting by reducing the violation count from 2%, in the nonforecast case, to 0.4% (for a 6-min battery). Here, the forecast window length is varied from 10 to 40 min ahead, or 1 to 4 intervals. The results, in Fig. 13, show that there is negligible improvement to increasing the window from 30 to 40 min ahead. When the window is decreased to only 20 min ahead, the performance worsens by about a factor of two. Finally, for a 10-min forecast, there is no additional gain over the nonforecasting controller in the present controller design due to the 10-min discretization interval of the controller. It is too late to proactively charge or discharge the battery, therefore power forecasting information 10 min ahead or less is not able to be

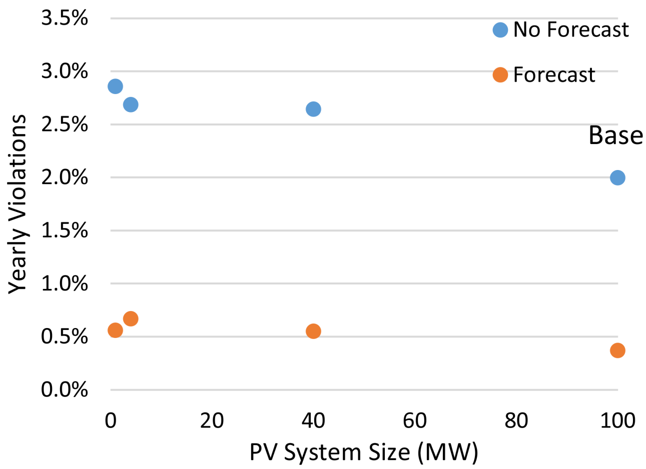

Fig. 14. Effects of varying system size (geographic smoothing).

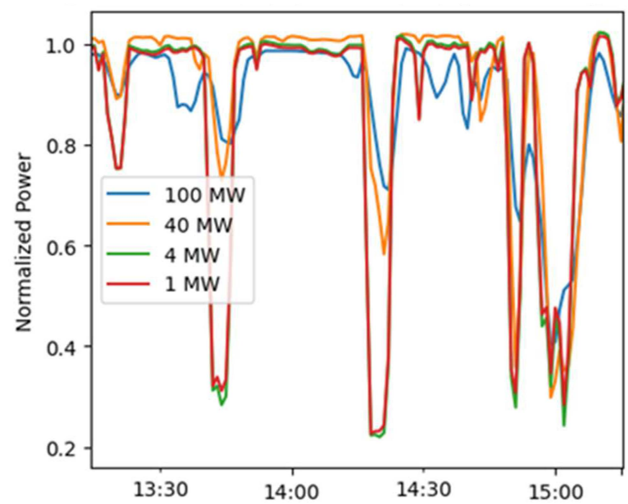

Fig. 15. Example profiles comparing variability in different size PV systems.

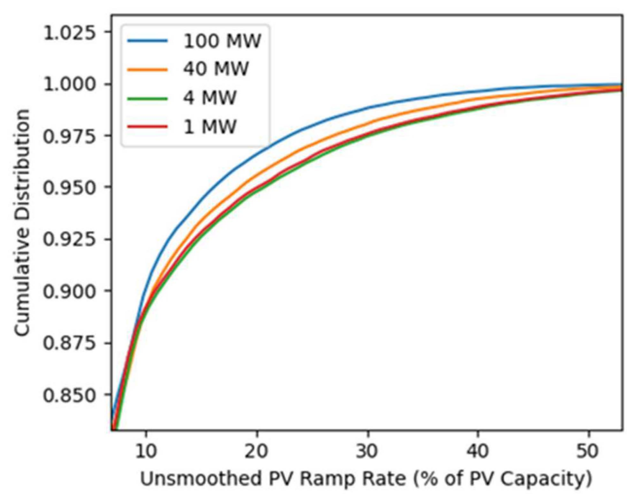

Fig. 16. Cumulative distributions of ramp rates in varying sized PV systems.

incorporated into the controller in the present design. Future designs could potentially address this shortcoming.

E. Impact of Geographic Smoothing

Geographic smoothing occurs in large PV plants. As clouds pass over and shade an array, it takes longer for the clouds to pass over systems with larger geographic areas. PV plants span roughly 4 acres per MW [24]. Geographic smoothing reduces fluctuations in PV output [5], which lessens the burden on storage. The effects of land area on irradiance variability have been studied and modeled in order to predict the variability of a plant with different areas [25]. In this article, the smoothing controller is applied to power production data from a single plant at varying levels of aggregation. The power production profiles from 1, 4, 40, and 100 MW sections of the PV plant are taken from the same time period, to control for weather and plant-specific differences. The performance of the smoothing controller is pictured in Fig. 14 for the varying plant sizes. Geographic smoothing at this level has a small to moderate effect on controller performance, as violations go from 2% in the 100 MW base case to around 2.75% in the 1 and 4 MW cases.

In examining the power profiles for the different sized arrays, varying ramping magnitudes are visible during variably cloudy days. Fig. 15 shows a 2-h window where the ramp magnitudes are more pronounced in the 1 and 4-MW sized arrays than in the 40 and 100-MW sized arrays. To get a sense of the full yearly difference, the cumulative distributions of ramp rates are shown in Fig. 16 for the different array sizes. There is a modest difference of about 2% in the distributions for ramp magnitudes from 10% to 40% in magnitudes. The higher prevalence in the smaller arrays leads to the increased number of violations.

F. Impact of Up-Ramp Curtailment

The final two cases under consideration involve loosening the requirements. In the first case, the system is allowed to simply curtail power during up-ramps rather than store the power. In the second case, the system is allowed to charge from the grid to return the SOC back to the resting value.

In this first case where curtailment is allowed to limit up-ramps, the storage no longer needs to leave a margin between the SOC and 100% since it never needs to respond to up-ramps by charging. By resting at full charge, the energy available to respond to down-ramps is effectively doubled for a given storage energy capacity. This is borne out in the results. In Fig. 17, both the nonforecasting (top figure) and forecasting (lower figure) cases, the controllers with curtailment reduce violations by a factor of two. The results corroborate what others have found, in that forecasting combined with up-ramp curtailment can nearly eliminate the need for storage altogether as in [21] and [26]. The downside of this approach is that energy is lost due to curtailment. An economic analysis is necessary to examine the viability of this approach. Furthermore, complications may arise from tax and other laws and contractual agreements that make the incentives of curtailment less attractive.

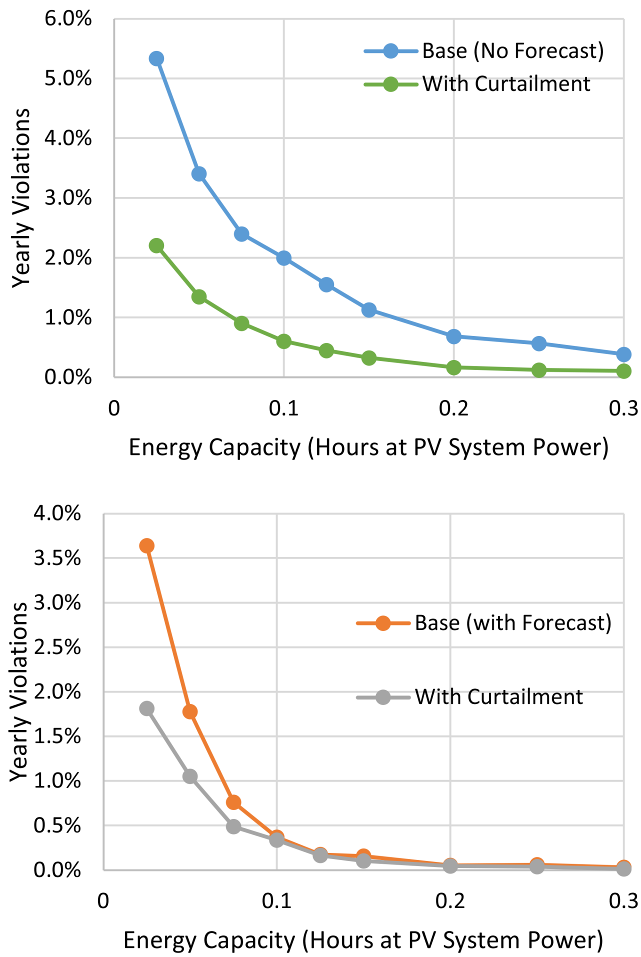

Fig. 17. Effects of allowing curtailment to control up-ramps.

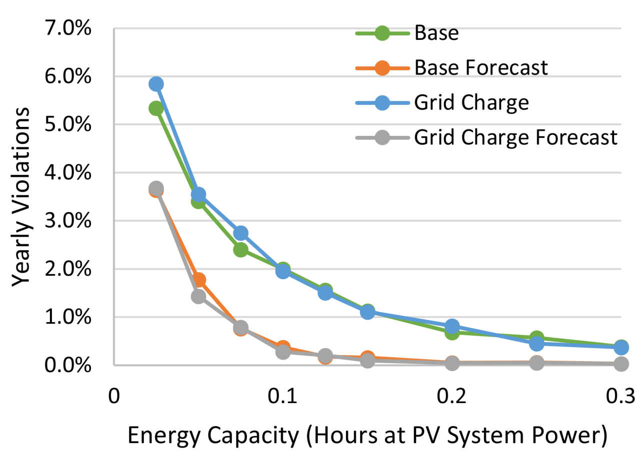

Fig. 18. Effects of allowing grid-charging.

G. Impact of Allowing Grid-Charging

The grid-charge constraint is a common challenge in PV plus storage systems that prevents storing energy taken from the grid. The idea behind relaxing the grid-charge constraint, in this application, is to allow the storage to return to the resting SOC overnight when there is no smoothing activity. The results, pictured in Fig. 18, show no improvement by relaxing this constraint, indicating that the grid-charging constraint is not limiting controller performance. The storage energy capacity is so small relative to the PV system that the SOC can somewhat easily be reset during a period of low-variability PV. Additionally, due to the generally symmetric nature of PV ramps during the day (more upward ramps in the morning, and more downward ramps in the evening), it is natural for the SOC to commonly end near 50% at the end of each day. Therefore, there is no need to allow charging from the grid.

VI. Conclusion

These results demonstrate that a relatively small amount of storage is needed to satisfy common PV smoothing requirements. Furthermore, short-term forecasting provides a substantial benefit for ramp rate mitigation, reducing the storage size needed. Yearly violations are reduced from 10% (with no storage) to 2% when using a storage system with 0.1 h (6 min) of energy capacity. When 30-min ahead PV power forecasting is utilized, the yearly violations are further reduced to 0.4% of the intervals. This result is consistent with the results of others who studied similar ramp rate control applications. Researchers in [14] found that a capacity of 6–10 min is required when limiting ramp rates to 10% per minute. A direct comparison cannot be made to the results of others since the underlying data and the specific system constraints are not the same. The value of this article is the accessibility of the control algorithm, through SAM, and the underlying data.

When compared to other applications like firming and peak shifting, the storage requirements for ramp rate smoothing are small. In 2019, the national average duration for all operating large-scale battery systems was 2.3 h, with an average duration in PJM of 45 min compared to 4 h in CAISO [27]. With such large energy capacities, there is an opportunity for storage systems to dedicate a relatively small fraction of capacity to performing ramp rate smoothing. Alternatively, short duration storage technologies with high cycle lifetimes, such as flywheels or electric double-layer capacitors, could be utilized for ramp rate smoothing, as others have investigated [12], [13].

Due to the relative infrequency of very high-magnitude ramp rates, above around 20%, in the unsmoothed PV power profile, there is diminishing returns to increasing the size of the storage power capacity beyond 20% of the PV system capacity. The forecast window length 30 min was shown to be an inflection point, as longer look-ahead forecasts did not further increase the controller performance. The effects of geographic smoothing were modest when comparing a 1-MW array to a 100-MW array, as violations are reduced by about a third (2.75% to 2%). Finally, if curtailment of energy is allowed when limiting the rate of increase of PV power, the storage energy capacity required can be approximately cut in half.

This presented approach provides a baseline approximation for the storage requirements of ramp rate mitigation. This baseline is useful for system planners and designers. The controller is posted publicly [22] and has been incorporated into system advisor model (SAM), version December 2, 2021.

REFERENCES

[1] W. Jewell and R. Ramakumar, "The effects of moving clouds on electric utilities with dispersed photovoltaic generation," in *IEEE Trans. Energy Convers.*, vol. EC-2, no. 4, pp. 570–576, Dec. 1987, doi: 10.1109/TEC.1987.4765894.1987.

[2] W. T. Jewell and T. D. Unruh, "Limits on cloud-induced fluctuation in photovoltaic generation," *IEEE Trans. Energy Convers.*, vol. 5, no. 1, pp. 8–14, Mar. 1990, doi: 10.1109/60.50805.

[3] J. Marcos et al., "Power output fluctuations in large scale PV plants: One year observations with one second resolution and a derived analytic model," *Prog. Photovolt., Res. Appl.*, vol. 19, pp. 218–227, 2011.

[4] S. Sukumar et al., "Ramp-rate control approach based on dynamic smoothing parameter to mitigate solar PV output fluctuations," *Int. J. Elect. Power Energy Syst.*, vol. 96, pp. 296–305, 2018.

[5] S. Shivashankar et al., "Mitigating methods of power fluctuation of photovoltaic (PV) sources–a review," *Renew. Sustain. Energy Rev.*, vol. 59, pp. 1170–1184, 2016.

[6] J. Martins et al., "Comparative study of ramp-rate control algorithms for PV with energy storage systems," *Energies*, vol. 12, no. 7, 2019, Art. no. 1342.

[7] V. Gevorgian and S. Booth, "Review of PREPA technical requirements for interconnecting wind and solar generation," 2013. [Online]. Available: https://www.nrel.gov/docs/fy14osti/57089.pdf

[8] ENERGINET, "Technical regulation 3.2.2 for PV power plants above 11 kW," Energinet.dk:, Fredericia, Denmark, 2016, pp. 1–111. [Online]. Available: https://en.energinet.dk/media/misfhs1q/technical-regulation-3_2_1-for-power-plants-up-to-and-including-11-kw.pdf

[9] A. Sangwongwanich, Y. Yang, and F. Blaabjerg, "A cost-effective power ramp-rate control strategy for single-phase two-stage grid-connected photovoltaic systems," in *Proc. IEEE 8th Annu. Energy Convers. Congr. Expo.*, 2016, pp. 1–7, doi: 10.1109/ECCE.2016.7854671.

[10] D. Kumar, S. Maharjan, and A. Srinivasan, "Ramp-rate limiting strategies to alleviate the impact of PV power ramping on voltage fluctuations using energy storage systems," *Sol. Energy*, vol. 234, pp. 377–386, 2022.

[11] S. Sukumar et al., "Ramp-rate control smoothing methods to control output power fluctuations from solar photovoltaic (PV) sources—a review," *J. Energy Storage*, vol. 20, pp. 218–229, 2018.

[12] N. Kakimoto, H. Satoh, S. Takayama, and K. Nakamura, "Ramp-rate control of photovoltaic generator with electric double-layer capacitor," *IEEE Trans. Energy Convers.*, vol. 24, no. 2, pp. 465–473, Jun. 2009, doi: 10.1109/TEC.2008.2001580.

[13] T. Monai, I. Takano, H. Nishikawa, and Y. Sawada, "A collaborative operation method between new energy-type dispersed power supply and EDLC," *IEEE Trans. Energy Convers.*, vol. 19, no. 3, pp. 590–598, Sep. 2004, doi: 10.1109/PSCE.2006.296448.

[14] J. Marcos et al., "Storage requirements for PV power ramp-rate control," *Sol. Energy*, vol. 99, pp. 28–35, 2014.

[15] T. D. Hund, S. Gonzalez, and K. Barrett, "Grid-tied PV system energy smoothing," in *Proc. IEEE 35th Photovolt. Specialists Conf.*, 2010, pp. 2762–2766, doi: 10.1109/PVSC.2010.5616799.

[16] R. K. Lam and H.-G. Yeh, "PV ramp limiting controls with adapative smoothing filter through battery energy storage system," in *Proc. IEEE Green Energy Syst. Conf.*, 2014, pp. 55–60, doi: 10.1109/IGESC.2014.7018640.

[17] A. Ellis, D. Schoenwald, J. Hawkins, S. Willard, and B. Arellano, "PV output smoothing with energy storage," in *Proc. IEEE 38th Photovolt. Specialists Conf.*, 2012, pp. 001523–001528, doi: 10.1109/PVSC.2012.6317885.

[18] Y. Huo and G. Gruosso, "A novel ramp-rate control of grid-tied PV-Battery systems to reduce required battery capacity," *Energy*, vol. 210, 2020, Art. no. 118433.

[19] A. Ryu, H. Ishii, and Y. Hayashi, "Battery smoothing control for photovoltaic system using short-term forecast with total sky images," *Elect. Power Syst. Res.*, vol. 190, 2021, Art. no. 106645.

[20] A. Kumler, Y. Xie, and Y. Zhang, "A new approach for short-term solar radiation forecasting using the estimation of cloud fraction and cloud albedo," 2018. [Online]. Available: https://www.nrel.gov/docs/fy19osti/72290.pdf

[21] X. Chen, Y. Du, H. Wen, L. Jiang, and W. Xiao, "Forecasting-based power ramp-rate control strategies for utility-scale PV systems," *IEEE Trans. Ind. Electron.*, vol. 66, no. 3, pp. 1862–1871, Mar. 2019, doi: 10.1109/TIE.2018.2840490.

[22] PV Ramp Rate Smoothing. GitHub, 2021. [Online]. Available: https://github.com/epri-dev/PV-Ramp-Rate-Smoothing

[23] N. Pilot et al., "Techno-economic analysis of novel PV plant designs for extreme cost reductions," in *Proc. IEEE 48th Photovolt. Specialists Conf.*, 2021, pp. 1258–1265, doi: 10.2172/1821823.

[24] M. Bolinger and G. Bolinger, "Land requirements for utility-scale PV: An empirical update on power and energy density," *IEEE J. Photovolt.*, vol. 12, no. 2, pp. 589–594, Mar. 2022, doi: 10.1109/JPHOTOV.2021.3136805.

[25] M. Lave, J. Kleissl, and J. S. Stein, "A wavelet-based variability model (WVM) for solar PV power plants," *IEEE Trans. Sustain. Energy*, vol. 4, no. 2, pp. 501–509, Apr. 2013, doi: 10.1109/TSTE.2012.2205716.

[26] M. Saleh, L. Meek, M. A. S. Masoum, and M. Abshar, "Battery-less short-term smoothing of photovoltaic generation using sky camera," *IEEE Trans. Ind. Inform.*, vol. 14, no. 2, pp. 403–414, Feb. 2018, doi: 10.1109/TII.2017.2767038.

[27] *Battery Storage in the United States: An Update on Market Trends*. Washington DC, 2021. [Online]. Available: https://www.eia.gov/analysis/studies/electricity/batterystorage/pdf/battery_storage_2021.pdf