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A Transparent BESS Sizing Framework for Ramp-Rate Control of a 100 MW Solar PV Plant Using SoDa Synthetic Power Profiles

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Abstract

Background: The integration of utility-scale solar photovoltaic power plants requires attention to short-term power fluctuations because photovoltaic output can change rapidly due to variations in irradiance, temperature, atmospheric conditions, and cloud movement.
Objective: This study aims to evaluate a SoDa-based synthetic photovoltaic power profile and optimize Battery Energy Storage System capacity for ramp-rate control of a 100 MW solar photovoltaic power plant.
Methods: A quantitative simulation and optimization approach was applied. A one-minute synthetic photovoltaic power profile was generated using SoDa, evaluated for monthly consistency against NASA POWER, and analyzed under multiple ramp-rate limit scenarios. The optimum BESS power and energy capacities were determined using deterministic grid search and benchmarked against Particle Swarm Optimization (PSO).
Results: The synthetic profile demonstrated adequate monthly consistency with NASA POWER (Pearson r = 0.860, rRMSE = 5.99%), confirming its suitability for pre-feasibility ramp-rate analysis. Stricter ramp-rate limits produced markedly more violations and required higher BESS capacities, ranging from 10 MW/10 MWh for moderate limits up to 20.5 MW/20.5 MWh for the most stringent scenario, with 100% compliance achieved in all cases. This framework demonstrates the practical value of synthetic data-driven BESS sizing for early-stage solar project planning in data-scarce environments.
Conclusion: Stricter ramp-rate limits increase BESS capacity requirements once the minimum capacity constraint is no longer sufficient. This study contributes an auditable, transparent pre-feasibility framework that integrates synthetic data generation, and advancing the literature on data-driven energy storage sizing for utility-scale solar PV projects.

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INTRODUCTION

The global transition to low-carbon electricity systems has accelerated the development of renewable energy generation, especially photovoltaic solar power plants or solar power plants (2025a). Solar PV is one of the dominant technologies in adding new generation capacity because it is modular, relatively fast to build, and increasingly competitive in terms of cost. However, the operational value of solar PV is not only determined by the annual energy produced. As solar PV penetration increases, short-term variability becomes an increasingly important planning and operation issue as the power injected into the grid can change rapidly due to variations in irradiation, temperature, cloud movement, and local atmospheric conditions (Bunn et al., 2024; Lave & Kleissl, 2011). In utility-scale solar PV, such changes occur on the order of megawatts and may require additional sources of flexibility to maintain a smoother power injection profile. It is important to note that the 100 MW plant capacity used in this study serves as a representative case study for utility-scale solar integration analysis; the proposed framework is not inherently limited to this specific capacity and can be adapted to other plant sizes with appropriate parameter adjustments.

Ramp-rate control is one of the direct approaches to deal with short-term solar power variability (Fregosi et al., 2023; Marcos et al., 2014). Ramp-rate indicates the rate of change in power over a given time interval, generally expressed in MW/minute or percentage of installed capacity per minute. When solar PV output increases faster than acceptable limits, energy storage systems can absorb some of that power gain. Conversely, when solar PV output drops rapidly, storage systems can inject power to compensate for the decline. The Battery Energy Storage System (BESS) is technically suitable for this function because it is capable of responding quickly and working bi-directionally (Amorim et al., 2024; Vega–Garita et al., 2024). However, determining the capacity of a BESS is not a simple matter: a BESS that is too small can fail to meet the ramp-rate limit, while a BESS that is too large increases the cost of investment without comparable technical benefits.

The main methodological challenge in this study is the availability of high-resolution data. Ramp-rate analysis requires short time intervals, ideally minute or sub-minute resolution data, as fluctuations due to cloud movement can be smoothed out or not recorded when using hourly, daily, or monthly data (Bright et al., 2015; Lave & Kleissl, 2011; Salazar-Peña et al., 2023). In many pre-feasibility studies, especially in developing or tropical regions, measurable irradiation data or actual solar power output at one-minute resolution are not yet available. This creates a gap between the data resolution required for BESS sizing and the data resolution that is generally available in the early stages of project development. Synthetic solar data generation tools can be a practical approach to fill the gap, provided the resulting profiles are evaluated first before being used as input for technical decisions. Previous studies have addressed sub-aspects of this challenge in isolation: some focused on irradiance downscaling without evaluating profile suitability for BESS optimization (Bright et al., 2015; Salazar-Peña et al., 2023), while others performed BESS sizing using measured data unavailable at pre-feasibility stages (Amorim et al., 2024; Vega–Garita et al., 2024). A framework that explicitly bridges high-resolution synthetic data generation, consistency verification, and transparent optimization in a single auditable workflow remains underrepresented in the literature (et al., 2018; Shahcheraghian et al., 2024) .

This study uses SoDa as an irradiance-based synthetic solar data generation tool to produce a one-minute resolution solar power profile (Carreño et al., 2020; Lajić et al., 2024). The use of synthetic data is not intended to replace field measurements or site-specific validation. In this study, synthetic data is positioned as a pre-feasibility approach when high-resolution measurement data are not yet available. Therefore, synthetic profiles should be treated with caution: they need to be checked in terms of data completeness, annual and monthly energy fairness, and ramp-rate characteristics before being used for BESS optimization. NASA POWER is used as a climatological reference on a monthly scale to evaluate whether the seasonal pattern of synthetic PV output is still reasonable (Sengupta et al., 2018; 2025b).

The second gap discussed in this study is related to optimization transparency. Many BESS sizing studies use advanced optimization methods, but initial planning also requires methods that are reproducible, easy to audit, and easy to explain to engineers, regulators, or project stakeholders. Since the decision variables in this study are limited to BESS power capacity and BESS energy capacity, deterministic grid search is suitable to be used as the main optimization method (Bergstra & Bengio, 2012; Rimal et al., 2024). This method evaluates the combination of candidates explicitly, applies the same technical constraints to each candidate, and selects viable candidates with the lowest annual cost. Particle Swarm Optimization (PSO) is not used to replace grid search, but as a comparative method to evaluate whether deterministic solutions are consistent with population-based metaheuristic approaches (Freitas et al., 2020;

Kennedy, 2010; Poli et al., 2007; Priyadarshi & Kumar, 2025). The importance of transparency in energy system planning has been widely recognized: Pfenninger et al. (2018) argue that open, auditable modelling approaches are essential for building stakeholder trust and enabling policy review, while Mavromatidis et al. (2018) demonstrate that traceable optimization methods help decision-makers understand and communicate sizing rationale under uncertainty both of which are critical requirements during pre-feasibility studies for utility-scale solar integration (Shahcheraghian et al., 2024).

The local relevance of this research lies in the need to support utility-scale solar PV planning in Indonesia, when solar potential is high but high-resolution site-specific measurements are not always available at the initial planning stage (Garniwa et al., 2024; Harsarapama et al., 2020). Broader relevance also applies to tropical power systems and other developing countries that face similar data limitations. In that context, a transparent and conservative pre-feasibility framework is more useful than black-box optimization results, as planning decisions must be traceable, technically accountable, and appropriately limited in claims. The results of the synthetic profile-based study should not be interpreted as a final interconnection design, but as the basis for initial sizing and identification of the sensitivity of BESS needs to ramp-rate assumptions.

The novelty of this research does not lie in the development of new irradiation models or new optimization algorithms. The contribution of this research lies in the integration of SoDa-generated high-resolution PV profiles, monthly consistency evaluations, ramp-rate violation assessments, deterministic BESS sizing, and PSO-based benchmarking into a single auditable framework for PV-BESS initial planning. In contrast to prior BESS sizing studies that either rely on measured high-resolution data (Amorim et al., 2024; Fregosi et al., 2023) or employ advanced metaheuristics without explicit auditability (Montalà Palau et al., 2025; Vega–Garita et al., 2024), the present framework is deliberately designed for data-scarce pre-feasibility contexts, combining data transparency at each stage with a deterministic optimization method that can be fully traced and replicated by engineering practitioners and regulatory reviewers. Within that framework, this article answers three research questions embedded in the narrative flow: whether SoDa synthetic profiles are consistent enough for pre-feasibility ramp-rate analysis, how PV profiles violate various ramp-rate limits prior to BESS implementation, and how much power and energy capacity of BESS is required to achieve full compliance with ramp-rate limits in scenarios R20, R10, R5, and R3.

Based on these questions, the following research propositions are advanced: (i) the SoDa-generated synthetic PV profile will exhibit sufficient monthly consistency with NASA POWER climatological data to serve as a valid input for pre-feasibility ramp-rate analysis; (ii) stricter ramp-rate limits will produce disproportionately higher violation counts, necessitating greater BESS capacities; and (iii) deterministic grid search will yield BESS sizing results consistent with those of PSO, confirming the robustness of the transparent optimization approach. The expected benefits of this study include: providing a replicable and auditable methodology for BESS pre-sizing that reduces reliance on unavailable measured data; enabling sensitivity analysis of ramp-rate assumptions during early project development stages; and demonstrating a transferable workflow applicable to other tropical regions with similar data constraints.

METHOD

This study used a quantitative approach based on simulation and optimization. The object of the study was a hypothetical utility-scale solar power plant with a capacity of 100 MWac located in Mekarwaru, Subang, West Java, Indonesia, at a latitude of -6.58558 and longitude of 107.89692. The selected generation capacity represented utility-scale solar integration, where short-term output variations could result in ramp events measured in MW/minute. Synthetic PV profiles were generated for 2020 using SoDa through the implementation of the original SoDa stochastic model. The initial source data were obtained from NSRDB/Himawari at 30-minute intervals and then converted into baseline PV output using PySAM PVWatts. The baseline output was subsequently downscaled by SoDa to a one-minute high-resolution power profile. The modeled system used a DC/AC ratio of 1.10, a tilt angle of 10 degrees, an azimuth of 0 degrees, a solar inverter efficiency of 96%, system losses of 14%, and a fixed open-rack configuration. Stochastic generation used a fixed seed of 42 to maintain reproducibility.

Before being used for BESS sizing, the profile was evaluated in terms of data completeness, energy metrics, and monthly comparisons with NASA POWER. Data quality indicators included the number of timesteps, missing values, duplicate timestamps, negative values, maximum PV power, annual energy, and capacity factor. SoDa monthly energy was compared with NASA POWER monthly all-sky GHI after the NASA monthly pattern had been scaled to match SoDa's total annual energy. This evaluation was not treated as field validation because one-minute measured solar power data were not available at the study site. Instead, the evaluation was used as a consistency check to determine whether the synthetic profile was sufficiently reasonable to serve as an input for ramp-rate analysis and BESS sizing at the pre-feasibility stage.

The ramp rate was calculated as the absolute difference between two consecutive one-minute PV power values, following ramp-rate control logic commonly used in PV smoothing studies (De La Parra et al., 2015; Marcos et al., 2014). Since the output resolution was one minute, the ramp-rate value could be directly expressed in MW/minute. Four ramp-rate scenarios were evaluated, namely R20, R10, R5, and R3, corresponding to 20%, 10%, 5%, and 3% of installed solar capacity per minute, respectively. For a 100 MW solar PV system, these limits were equivalent to 20, 10, 5, and 3 MW/minute. R20 was used as a regulatory reference scenario aligned with the Indonesian grid code requirement under Permen ESDM No. 20/2020, while R10, R5, and R3 were used as technical sensitivity scenarios reflecting internationally observed ramp-rate requirements, including those in Australia, Japan, and various European jurisdictions. These scenarios enabled the evaluation of the effect of increasingly stringent ramp-rate limits on BESS capacity requirements across a range of regulatory environments (Montalà Palau et al., 2025; Talvi et al., 2023; Peraturan Menteri Energi dan Sumber Daya Mineral Nomor 20 Tahun 2020 tentang Aturan Jaringan Sistem Tenaga Listrik, 2020).

The BESS was modeled as a bidirectional device for active power smoothing. Positive BESS power represented discharge or power injection into the network, while negative BESS power represented charging or power absorption. The network power at each timestep was calculated as the sum of PV power and BESS power. When PV power increased faster than the ramp-rate limit, the BESS charged to absorb the excess power increase. Conversely, when PV power decreased faster than the limit, the BESS discharged to compensate for the power decrease. BESS operation was constrained by a minimum state of charge (SOC) of 20%, a maximum SOC of 90%, a target SOC of 55%, a round-trip efficiency of 95%, a maximum C-rate of 1C, and a requirement that no ramp-rate violations occur after BESS integration. The minimum BESS power capacity was set at 10% of the installed solar power capacity, equivalent to 10 MW for a 100 MW solar PV system. Since the C-rate limit was 1C, the minimum effective energy capacity was also 10 MWh.

The objective function of the optimization was to minimize annual costs while satisfying all technical constraints. The BESS investment cost was separated into power-based and energy-based components, amounting to USD 427,420/MW and USD 307,990/MWh, respectively, following the power-energy cost structure commonly used in utility-scale battery studies (Cole & Karmakar, 2023; Laboratory, 2024). The annual cost was calculated using a discount rate of 8%, a project life of 20 years, and a fixed operation and maintenance cost of 2.07% per year, using a capital recovery factor formulation (Kandpal et al., 2024; Short et al., 1995). A deterministic grid search was used as the primary optimization method by evaluating candidate combinations of BESS power and energy capacities over a predefined range and selecting the viable candidate with the lowest annual cost. Particle Swarm Optimization (PSO) was used as a comparison method, using the same PV inputs, BESS control logic, constraints, and cost assumptions. PSO solution candidates were rounded up to 0.1 MW or 0.1 MWh to enable comparison with the results of the fine-grid search.

This study did not involve human or animal participants and therefore did not require ethical approval. All data were processed in accordance with the institution's academic integrity standards.

RESULTS AND DISCUSSION

Results

SoDa Synthetic PV Power Profile Generation Results

The final SoDa profile consists of 525,600 one-minute timesteps from January 1, 2020 at 00:00 to December 31, 2020 at 23:59, with a non-leap calendar. No missing values, duplicate timestamps, or negative power values were found. The maximum PV power reached 87,966 MW and remained below the generating capacity of 100 MW, while the annual energy was 141,513.904 MWh. This value is equivalent to a capacity factor of 16.155%. A monthly consistency evaluation of NASA POWER yielded a Pearson correlation of 0.860 for monthly energy distribution and a relative rRMSE of 5.992%, indicating that the seasonal pattern of the synthetic profile is quite aligned with the independent monthly solar resource reference.

Table 1

Synthetic Power Profile

Indicator	Value	Unit/Description
Study location	Mekarwaru, Subang, West Jawa, Indonesia	Technical study location
Latitude	-6,58558	Degrees
Longitude	107,89692	Degrees
Simulation year	2020	Year
Calendar	Non-Leap	365 days
Initial NSRDB data interval	30	minutes
Solar Power Plant Capacity	100,0	MWac
DC/AC ratio	1,10	-
Tilt	10,0	Degrees
Azimuth	0,0	Degrees
Inverter efficiency	96,0	%
System Losses	14,0	%
Types of module arrangements	*fixed open rack*	PVWatts array type 0
Output resolution	1	minutes
Stochastic seed	42	-
Maximum power limit	100,0	MW

Based on Table 1, the synthetic PV power profile was generated for the Mekarwaru location, Subang, West Java (−6.58558°, 107.89692°) using 2020 NSRDB data with an initial resolution of 30 minutes which was then upgraded to a resolution of 1 minute, resulting in 525,600 data. The modeled system is a 100 MWac solar power plant with a DC/AC ratio of 1.10, tilt of 10°, azimuth of 0°, inverter efficiency of 96%, system loss of 14%, and configuration of fixed open rack modules. The resulting power profile is used as the basis for analyzing BESS capacity requirements for PLTS ramp-rate *control.*

Table 2

Summary of data quality and energy production of SoDa profiles

Indicator	Value	Units
Number of time series	525,600	Minute data
Initial time	2020-01-01 00:00:00	-
End time	2020-12-31 23:59:00	-
Time interval	0,016667	Hours
Missing value	0	References
Repeating time	0	References
Negative values	0	References
Zero value	264.738	References
PV maximum power	87.966	MW
Average power PV	16,155	MW
Annual energy	141.513,904	MWh/year
Capacity factor	16,155	%

Table 2 confirms data completeness and quality: the profile contains no missing, repeated, or negative values. With an annual energy of 141.51 GWh/year and a capacity factor of 16.155%, the profile forms the basis for subsequent ramp-rate analysis and BESS simulation.

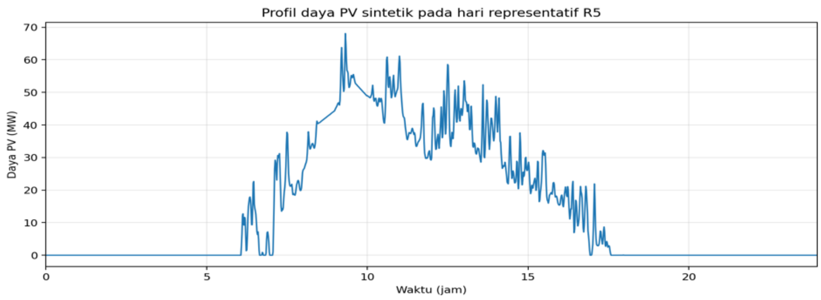

Figure 1. *Screenshot of SoDa synthetic PV power profile 1 minute resolution*

The profile shows a sharp change in power at some periods of daylight. This fast-changing character is why BESS analysis for power change rate control requires one-minute resolution data, not just daily or monthly data.

Evaluation of the Monthly Energy Consistency of the SoDa Profile to NASA POWER

A consistency evaluation of NASA POWER was carried out to verify the fairness of the monthly energy pattern of the SoDa profile by comparing the monthly energy of SoDa to the GHI NASA POWER pattern which has been scaled to the total annual energy of SoDa so that it can be expressed in MWh/month. In addition, the monthly distributions of the two are compared based on the percentage contribution to the total annual energy to assess the suitability of seasonal patterns. Prior to the comparison, the calendar was aligned by removing the date February 29, 2020 from the NASA POWER data to match the SoDa profile that uses a 365-day non-leap calendar. This approach allows evaluation both in terms of energy amount and seasonal variation patterns between months.

Table 3

Comparison of SoDa monthly energy and scaled NASA POWER patterns

Month	SoDa (MWh)	NASA GHI (kWh/m2/month)	NASA Scaled (MWh)	SoDa Difference - NASA (MWh)	Difference (%)
Jan	10.118,49	135,56	10.872,55	-754,06	-6,94
Feb	9.223,82	113,94	9.139,07	84,74	0,93
Maret	11.914,79	150,16	12.043,54	-128,75	-1,07
Apr	11.899,37	144,07	11.555,33	344,03	2,98
May	11.813,40	137,28	11.011,18	802,22	7,29
June	12.479,89	142,89	11.460,59	1.019,30	8,89
Jul	13.024,09	151,14	12.122,21	901,88	7,44
Aug	13.844,17	165,85	13.302,42	541,75	4,07
Sep	13.640,81	175,65	14.088,25	-447,44	-3,18
Oct	12.390,42	157,66	12.645,21	-254,79	-2,01
Nov	11.176,88	152,93	12.266,11	-1.089,23	-8,88
Dec	9.987,78	137,24	11.007,45	-1.019,66	-9,26

Note: NASA scaled means that the GHI NASA POWER pattern is normalized to total annual SoDa energy so that it can be read in MWh/month. Positive values indicate SoDa is higher than NASA's scaled pattern.

Based on Table 3, the monthly pattern of SoDa generally follows the seasonal variation of NASA POWER after scaling. However, there are differences in some months. SoDa tends to be higher than NASA's scaled pattern in May, June, July, and August, while lower in January, September, November, and December. This difference is natural because NASA POWER represents horizontal GHI, while SoDa produces synthetic AC PV power that is influenced by the PV model, system loss, temperature, wind, module orientation, and cloud stochastic model.

Table 4
Summary of SoDa consistency evaluation metrics against NASA POWER

Metrics	Value	Units
Number of months	12	Months
SoDa annual energy	141.513,904	MWh/year
NASA POWER Annual GHI	1.764,352	kWh/m2/year
SoDa specific results	1.415,139	kWh/kWp/year
Implicit performance ratio	80,207	%
Pearson correlation of monthly distribution	0,860	-
RMSE monthly distribution	0,499	Percentage
MAE monthly distribution	0,435	Percentage
rRMSE monthly distribution	5,992	%
NASA's energy RMSE scaled	706,598	MWh/month
Maximum positive difference	1.019,296	MWh/month
Maximum negative difference	-1.089,226	MWh/month

The Pearson correlation value of 0.860 and the rRMSE of 5.992% indicate that the SoDa profile has a good monthly pattern fit with NASA POWER, making it suitable for use as an input for ramp-rate analysis and BESS capacity determination. However, these results are an evaluation of pattern consistency, not a validation of field measurement data.

Evaluation of Ramp-rate Statistics Before BESS

Ramp-rate analysis prior to BESS showed that the average absolute ramp was relatively low, at 0.394 MW/minute, but the tail part of the distribution contained a much larger event. The value of P99 reached 4,242 MW/minute, P99.9 reached 7,595 MW/minute, and the maximum ramp reached 16,474 MW/minute. This suggests that BESS sizing cannot be based solely on the average value of the ramp because short-term extreme events determine whether the power output violates a particular ramp-rate limit.

Table 5
PV Ramp-rate and Breach Statistics Before BESS

Metrics	Value	Units
Number of power change events	525.599	Events
Absolute average	0,394	MW/min
Absolute standard deviation	0,869	MW/min
P90 / P95	1,246 / 2,102	MW/min
P99 / P99.9	4,242 / 7,595	MW/min
Maximum	16,474	MW/min
R20 Violation	0	Events
R10 Violation	104	Events
R5 Violations	3.033	Events
R3 Violations	13.175	Events

The R20 scenario does not result in a violation because the maximum ramp is lower than 20 MW/min. When the limit was tightened to R10, R5, and R3, the number of violations increased to 104, 3,033, and 13,175 incidents. This pattern confirms that the need for BESS is greatly influenced by the level of tightness of the ramp-rate limit. R20 is a relatively loose case for the analyzed profile, while R5 and R3 are more technically demanding scenarios.

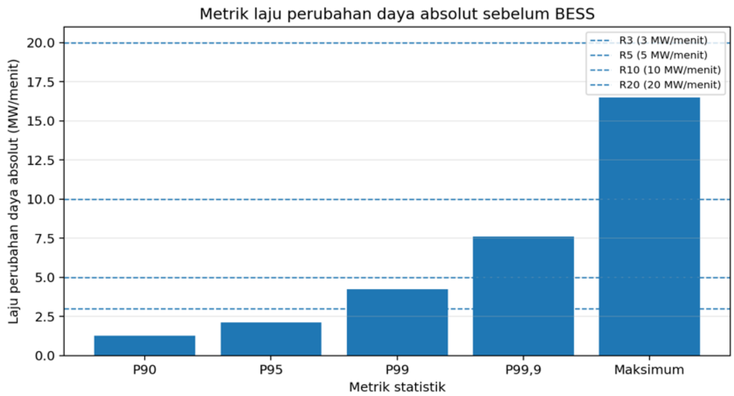

Figure 2. *Ramp-rate metric before BESS*

BESS Optimization Results

Deterministic grid search results in viable BESS capacity for all ramp-rate scenarios. For R20 and R10, the optimum capacity is 10 MW/10 MWh. For R20, this capacity is mainly determined by the minimum constraint of BESS power, not by actual smoothing needs, since prior to BESS there was no ramp-rate violation. At R10, the same minimum capacity is enough to eliminate all 104 initial violations. When the limit is tightened to R5, the optimum capacity increases to 16 MW/16 MWh. In the most stringent scenario R3, the optimum capacity increases again to 20.5 MW/20.5 MWh. All scenarios achieve 100% compliance after the implementation of BESS.

Table 6

Results of BESS Capacity Optimization in Various Ramp-Rate Scenarios

Scenario	Limit (MW/min)	P_BESS (MW)	E_BESS (MWh)	Duration (minutes)	Annual fee (million USD/year)	LCOS (USD/MWh)	Compliance (%)
R20	20,0	10,0	10,0	60,0	0,901	not counted	100,000
R10	10,0	10,0	10,0	60,0	0,901	546.469,24	100,000
R5	5,0	16,0	16,0	60,0	1,442	23.750,51	100,000
R3	3,0	20,5	20,5	60,0	1,848	6.331,54	100,000

Table 6 shows a clear relationship between ramp-rate limits and optimal BESS capacity. Annual costs follow the same pattern, increasing from 0.901 million USD/year in the case of minimum capacity to 1.442 million USD/year in R5 and 1.848 million USD/year in R3. The results also show that power capacity and energy capacity are of equal value across all optimal scenarios. This is a direct consequence of the maximum C-rate constraint of 1C, which requires that the energy capacity in MWh is at least equal to the power capacity in MW.

PSO comparison was conducted to test whether the results of deterministic grid search were consistent with alternative optimization methods. PSO results are identical to grid search results in all scenarios. The difference in power capacity, energy capacity, and annual cost is zero for R20, R10, R5, and R3. This confirms that the deterministic grid search solution is not just an artifact of a single search method.

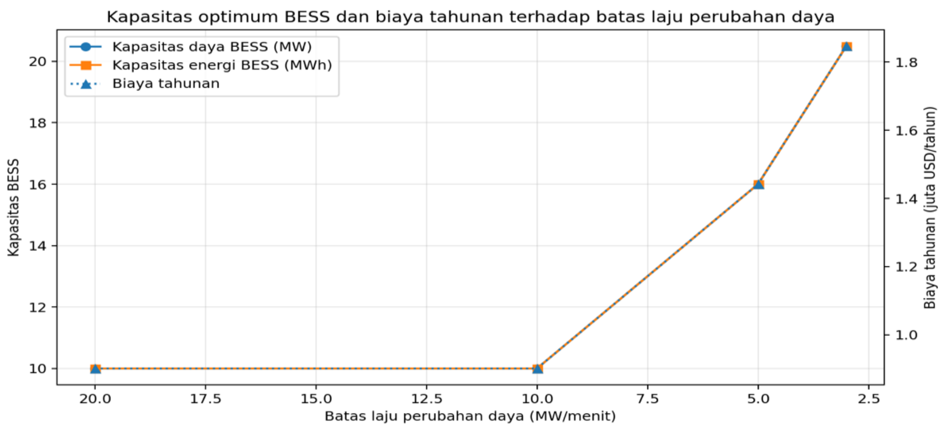

Figure 3. *Optimum capacity of BESS and annual cost to ramp-rate limits*

Table 7

Comparison of Deterministic Grid Search and PSO results

Scenario	P grid (MW)	P PSO (MW)	ΔP (MW)	E grid (MWh)	E PSO (MWh)	ΔE (MWh)	Δ cost (USD/year)	PSO time(s)
R20	10,0	10,0	0,0	10,0	10,0	0,0	0,00	10,70
R10	10,0	10,0	0,0	10,0	10,0	0,0	0,00	11,32
R5	16,0	16,0	0,0	16,0	16,0	0,0	0,00	11,43
R3	20,5	20,5	0,0	20,5	20,5	0,0	0,00	11,30

The operational performance after BESS also shows that the optimum capacity is sufficient in terms of meeting constraints. In R5, the annual discharge energy reached 60.715 MWh and the annual charge energy reached 64.167 MWh, with the SOC maintained in the range of 47.276% to 63.379%. In R3, annual discharge energy increased to 291,807 MWh and annual charge energy increased to 308,090 MWh, with SOC in the range of 46,879% to 66,049%. The SOC range is still far within the operating limit of 20%-90%, so the energy constraint is not close to the lower or upper limit of the analyzed profile.

Evaluation of BESS Operation Performance After Optimization

Once the optimum capacity is determined, the operating performance of the BESS is evaluated based on the maximum ramp-rate after BESS, the number of violations, the SOC range, the annual discharge energy, the annual charge energy, and the equivalent carbon emission indicator. This evaluation is necessary so that the optimum capacity is not only minimal in terms of cost, but also proven to meet all operational constraints throughout the one-year profile.

Table 8

BESS Operating Performance and CO2 Equivalent Indicators

Scenario	Ramp after BESS (MW/min)	Violations	SOC min (%)	max SOC (%)	Annual Discharge (MWh)	Annual charge (MWh)
R20	16,474	0	55.00	55.00	0,00	0,00
R10	10,000	0	49.62	56.20	1,64	1,22
R5	5,000	0	47.27	63.37	60,71	64,16
R3	3,000	0	46.87	66.04	291,80	308,09

Discussion

The first implication of the results of the study relates to the position of synthetic PV profiles in pre-feasibility studies. SoDa profiles should not be interpreted as a substitute for data on irradiation measurements or one-minute PV power in the field. Its main value is to provide a high-resolution profile that can be used technically when measurement data is not yet available. By evaluating the profile of NASA POWER on a monthly scale and examining the completeness of the data and ramp-rate statistics, this study does not treat synthetic data as field truths that do not need to be tested. This distinction is important to maintain academic and engineering credibility. The results support the use of SoDa as a pre-feasibility input, but not as a final validation of site-specific PV variability.

The second implication is that the tightness of the ramp-rate limit is a major driver of BESS needs. The same PV profile does not result in violations on R20, but results in thousands of violations on R5 and R3. Thus, the decision to implement stricter ramp-rate limits has direct technical and economic consequences. In the case analyzed, R20 does not require BESS when viewed only from ramp-rate violations, although the final optimization result remains 10 MW/10 MWh due to the assumption of minimum BESS capacity. This distinction is important: the capacity of the R20 needs to be read as the result of the minimum design constraint, not the actual smoothing requirement. On the contrary, the results of R5 and R3 show an increase in BESS capacity which is really due to the need to meet stricter ramp-rate limits.

One aspect that merits specific attention when compared with prior BESS studies is the equality of optimal power and energy capacities. While Amorim et al. (2024) and Montalà Palau et al. (2025) report configurations where energy capacity exceeds power capacity due to longer smoothing durations or degradation constraints, the present study yields E_BESS = P_BESS in all scenarios. This divergence reflects the 1C C-rate constraint and the relatively short duration of ramp-rate events in the analyzed tropical profile, suggesting that power capacity is the binding constraint under conservative pre-feasibility assumptions a result that may differ in profiles with more sustained cloud-induced ramp events. The repetitive similarities between the power and energy capacities of BESS also need to be interpreted carefully in relation to the power-energy coupling and C-rate constraints in BESS sizing (Amorim et al., 2024; Montalà Palau et al., 2025). These results do not mean that ramp-rate control intrinsically requires a one-hour storage duration. The similarity reflects the interaction between the C-rate constraint 1C and the objective function of cost minimization. Since candidates with E_BESS lower than P_BESS would violate the C-rate limit, the minimum-cost viable solution naturally chooses E_BESS equal to P_BESS when additional energy capacity is not required by SOC constraints. These findings suggest that in the analyzed control profiles and strategies, the BESS power capacity is more dominant in sizing, whereas the energy capacity is primarily required to maintain SOC operations feasible under the applied C-rate rules.

The methodological contribution of this research lies in the transparency of the optimization framework. In the matter of two-variable sizing, deterministic grid search is not an overly simple choice, but rather a method that can be accounted for because each solution candidate is explicitly evaluated and can be audited. This is relevant for initial planning when stakeholders need to trace the reasons for selecting a specific BESS capacity. The PSO results reinforce this conclusion because it results in the same optimal capacity across all scenarios. In this context, PSO serves as a consistency check, not a superior substitute for grid search. The similarity of results shows that the solution is quite robust to the search method when using the same data, constraints, and cost assumptions.

From a practical point of view, the proposed framework is relevant for PV-BESS planning in areas that have limited high-resolution data but still require a network integration study. This approach is also useful for comparing the impact of various ramp-rate assumptions before the project enters the detailed engineering design stage. However, this framework should be used with proper limitations. This study has not included battery degradation, multi-year resource variability, detailed financial analysis, market revenue, or actual network interconnection constraints. With respect to interannual variability, it is important to acknowledge that the optimized BESS capacities reported here are based on a single synthetic year 2020. Interannual variability in solar irradiance driven by El Niño–Southern Oscillation (ENSO) cycles, aerosol loading, and long-term climate trends can produce years with significantly higher ramp-rate frequencies or magnitudes (Pfenninger et al., 2018; Salazar-Peña et al., 2023). Therefore, the BESS capacities derived in this study should be interpreted as point estimates for the simulated year, not as robust multi-year design values. Further generalization of the results requires multi-year synthetic profiles or, preferably, actual measured power data from multiple operational years. Regarding practical integration into the feasibility study process, the proposed framework is designed to be executed as a structured sequence of steps compatible with standard pre-feasibility workflows. In practice, engineering teams can apply this framework at the resource assessment phase, prior to detailed layout design, by using available satellite-derived irradiance data (e.g., NSRDB, CAMS) as the source input for SoDa-based synthetic profile generation. The consistency evaluation against NASA POWER provides a documented quality gate before the profile is used for BESS sizing. The deterministic grid search output BESS power capacity, energy capacity, and annual cost under each ramp-rate scenario can then be directly incorporated as a sensitivity table in the pre-feasibility report, enabling project developers and financing institutions to assess the cost implications of different grid code requirements before committing to detailed engineering studies.

CONCLUSION

This study compiles and evaluates a transparent BESS capacity determination framework for the control of the ramp-rate of 100 MW solar power plants using a one-minute resolution SoDa synthetic power profile. The synthetic profile produces an annual energy of 141.51 GWh and a capacity factor of 16.15%, with a monthly correlation of 0.860 to NASA POWER and a monthly distribution rRMSE of 5.99%. These results suggest that the profile is fairly consistent for the pre-feasibility stage ramp-rate analysis, but it should still be interpreted as synthetic data, rather than field measurement data. Prior to the implementation of BESS, there were no violations on R20, while R10, R5, and R3 resulted in 104, 3,033, and 13,175 ramp-rate violations.

The results of the deterministic grid search show that the tightening of the ramp-rate limit increases the capacity requirement of BESS after the minimum capacity limit is no longer sufficient. The optimum capacity of BESS is 10 MW/10 MWh for R20 and R10, 16 MW/16 MWh for R5, and 20.5 MW/20.5 MWh for R3. All scenarios achieve 100% compliance after the implementation of BESS. PSO comparison results in identical capacities, thus strengthening the consistency of deterministic grid search solutions on the same technical and economic assumptions. The main contribution of this research is not a new optimization algorithm, but an auditable framework that connects the generation of high-resolution synthetic PV profiles, consistency evaluation, ramp-rate analysis, BESS control, and optimization into a practical initial planning flow.

Future research should extend this framework by: (i) replacing synthetic profiles with measured high-resolution irradiance or power data from operational solar plants for direct validation; (ii) incorporating multi-year resource datasets to account for interannual solar variability and improve sizing robustness; (iii) adding battery degradation models and detailed techno-economic variables for bankable feasibility studies; (iv) evaluating alternative BESS control strategies such as rolling-average smoothing and state-of-charge-aware dispatch; and (v) developing multi-objective optimization approaches that simultaneously minimize cost, maximize compliance, and reduce lifecycle carbon emissions. Such extensions would advance the initial framework proposed here into a comprehensive technical-economic and operational planning tool for utility-scale BESS integration in renewable-rich power systems.

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AUTHOR CONTRIBUTION STATEMENT

Muhammad Haikal Erniza Putra contributed to the conceptualization, methodology development, data analysis, simulation design, and preparation of the original manuscript. Faiz Husnayain contributed to research supervision, validation, technical review, refinement of the methodology, and critical revision of the manuscript. Both authors collaboratively contributed to the interpretation of findings, manuscript improvement, and final approval of the submitted version.

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