Cost of Violations in Ramp Rate Control in Photovoltaic (PV) Systems

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Abstract The increasing integration of solar photovoltaic (PV) systems and their generation variability has raised stability concerns with operators. Various Power Ramp Rate Control (PRRC) strategies are proposed to smooth out generation and maintain ramps below certain thresholds, but the cost of failing to do so remains unknown. This paper introduces a new metric to quantify the cost of excessive variability based on the energy these violations carry, which can be mapped to the grid ramping flexibility and serve as a penalty mechanism. This enables a coherent technoeconomic analysis of various forecasting- and battery-based PRRC alternatives. Results on a yearlong dataset with 1-second resolution identify the optimal battery size and show that invest-free forecasting-based approaches can also perform quite satisfactorily.

1 Introduction

In recent years, power grids have experienced a significant increase in the integration of solar photovoltaic (PV) systems, establishing solar PV as a promising and expanding renewable energy source. However, the high penetration levels and weather-dependent nature of PV generation present challenges to grid stability due to generation variability. Steep changes in power output, or high ramps, especially in small systems, can lead to frequency distortion, voltage oscillations, and power quality issues [1,2].

Ramp Rate (RR) is a widely adopted metric that quantifies the rate of change of power over time [1]. RR violations occur when the PV power ramp rate exceeds the grid's proposed maximum limits. Such violations are undesirable by system operators, but standardised penalties have not yet been established. As shown in the studies by Chen et al. (2019) and Chen et al. (2022), excessive ramp-rate violations increase the need for ancillary services and impose economic costs on utilities, motivating the development of forecasting-based control strategies [2,3]. Wen et al. (2021) highlight that without accurate prediction and mitigation, frequent violations can stress grid infrastructure and reduce the reliability of high PV penetration systems [4]. Therefore, it is important not only to reduce violations but also to quantify their cost and impact to the grid.

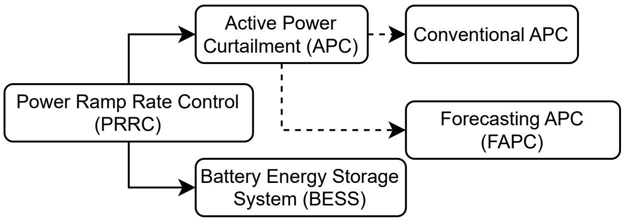

Fig. 1: Power Ramp-Rate Control (PRRC) methods.

To mitigate grid instability caused by RR violations, RR control methods are introduced by applying a regulated maximum RR limit set by grid operators [3,4]. Such power ramp rate control (PRRC) methods smooth out solar generation through active power curtailment or by integrating energy storage systems with a high-level classification in Fig. 1 [2].

Among them, the active power curtailment (APC) method, as shown in Fig. 2(a), is an invest-free approach that avoids additional capital costs by intentionally curtailing energy. In Fig. 2(a), the solid black line represents the actual PV generation, while the blue dashed line indicates the PV output after conventional APC. However, conventional APC methods are generally only capable of mitigating ramp-up events, leaving ramp-down fluctuations largely uncontrolled [2,4] (Fig.2a). To overcome this limitation, there is ongo-

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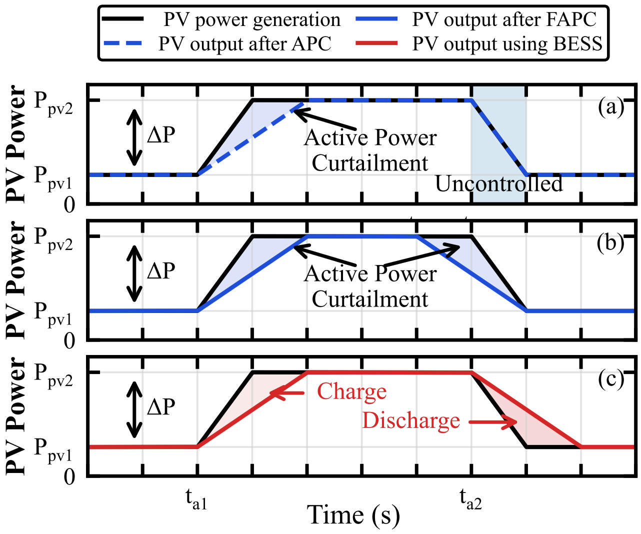

Fig. 2: PRRC approaches: (a) conventional APC, (b) forecasting-based APC/FAPC , and (c) BESS.

ing research on forecasting-based APC (FAPC) strategies. As illustrated in Fig. 2(b), now-casting in FAPC enables pre-emptive curtailment, thus catering for both ramp-up and ramp-down events. The alternative of a battery energy storage system (BESS) is shown in Fig. 2(c), where the PV output using an BESS is represented by the red line. In this case, surplus energy is absorbed during RR overshoots and released back during periods of power deficit through discharging (red line), resulting in a smoother generation without curtailments. This method maximises energy yield but at the cost of higher capital investment.

Table 1 summarises the methods and metrics to evaluate the violations impact in the literature; for example, Chen et al. [2,3] and Wen et al. [4] assessed ramp-rate violations by counting, percentages, ramp events, and failure rates. However, none of those papers linked these metrics to a quantifiable monetary value that could be used as penalty by operators and discourage violations. Pelaez et al. [5] proposed a fixed penalty per time step but without justification in a physical or economic sense. Most importantly, existing approaches centre around the multitude of violations but ignore the magnitude and intensity. There is still an unmet need for a transparent and justified violation metric that can serve as a penalty by operators and disincentive to RR violations.

Quantifying the violations cost can enable also proper planning with or without BESS. Few studies adopted the levelized cost of electricity (LCOE) to assess the economic performance of power ramp-rate control (PRRC) strategies [6,7,5]. For example, BESS-based PRRC usually incurs higher costs due to higher investment and short lifespan, whereas FAPC alternatives avoid capital investment at the expense of curtailing[6]; however, improved nowcasting can reduce both storage requirements and curtailment losses,

Table 1: Literature metrics on the cost of violations

Paper	Violation Metric	No of viol.*	Penalty	Physical meaning
Chen et al. 2019 [2]	Percentage Ramp violation	✓	weekly penalty using curtail	×
Chen et al., 2022 [3]	Ramp smoothing rate (RSR)	✓	×	×
Wen et al., 2021 [4]	Ramp Events, Failure rate (%)	×	×	×
Pelaez et al., 2021 [5]	Violation time penalty and percentage	✓	Fixed penalty per violation time	×
Proposed	**Energy Violation**	✓	**Upward/ Downward Eviol cost**	✓

*Number of Violations (N_{viol})

thereby lowering LCOE values [7]. Although Pelaez et al. account for the penalty costs of RR violations, the quantification and cost of energy violations remain unaddressed in LCOE [5]. To date, there is no study to evaluate the planning options for a PV system with PRRC capabilities considering the violation cost.

This paper aims to fill this gap by introducing a new RR violations metric and apply it to evaluate various PRRC options. The main contributions are as follows:

- Proposing the *Violation Energy* metric to quantify the cost of RR violations based on the surplus or deficit energy.
- Linking this metric to power system flexibility costs for a transparent and reliable penalty mechanism.
- Incorporating this penalty into the LCOE metric and assessment of various FPAC and BESS options.

2 Ramp-Rate Smoothing methods

Among the PRRC variants in Fig.1, the most promising options are FAPC and BESS. Although these methods are fundamentally different, they both aim to reduce violations and enhance grid flexibility [2–4,6]. Fig. 3 depicts these two strategies: the FAPC controller, which relies on power forecasting, and the BESS-based controller, which operates without forecasting. Although both strategies reduce violations, they introduce trade-offs in terms of energy curtailment, efficacy and violations, storage utilisation, which are analysed in the following subsections.

2.1 Forecasting Active Power Curtailment (FAPC)

FAPC anticipates ramp events using short-term power forecasting or nowcasting ranging from persistence models to more advanced deep learning approaches such as CNN, LSTM

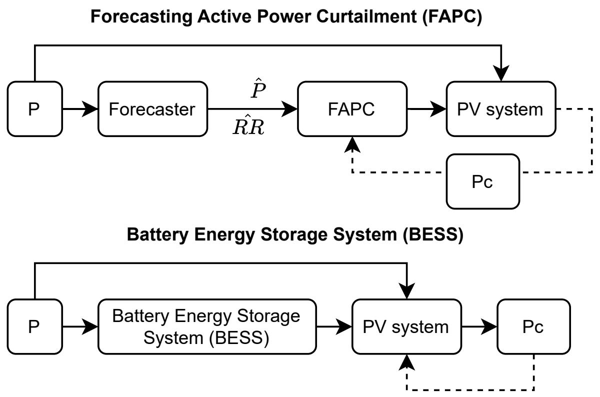

Fig. 3: Power ramp rate control methods classification.

architectures, and reduce violations through proactive generation curtailment [3,4]. Fig. 4 illustrates the proposed control strategy in the ideal case of a flawless forecaster. Fig.4(a) shows a snapshot of the power profile (P) highlighting the curtailment resulting from power control using the FAPC approach. The green dashed line represents the controlled power profile (P_c), while the red shaded area indicates the curtailed power. Fig.4(b) presents the RR, confirming control with the limits. Fig.4(c) shows a histogram of the controlled RR for a day indicating again the controlled RR distribution staying within limits.

To assess the impact of forecasting quality, two forecasting variants are considered: an ideal Perfect forecaster and a more practical but naive of persistence-based forecaster.

2.1.1 Perfect Forecaster (PF)

A perfect forecaster (ideal theoretical approach) assumes complete knowledge of the future and therefore introduces no prediction error. It serves here as the benchmark for FAPC methods. Although unrealistic in practice, it represents an ideal upper bound for comparing with realistic forecasters. For a prediction horizon H, the forecasted power equals the true future power:

$$\hat{P}_{t+k} = P_{t+k}, \qquad k = 1,2,\dots,H. \tag{1}$$

where P_t denotes the measured power at time step t, $\hat{P}_{t+k}$ is the forecasted power.

2.1.2 Persistence (Prs)

The persistence variant is the most naive method and widely adopted for baseline performance, in which future power values are assumed to remain constant and equal to the average of the most recent L observations. The forecast power $\hat{P}_{t+k}$ over a prediction horizon H is given by:

$$\hat{P}_{t+k} = \frac{1}{L}\sum_{i=0}^{L-1} P_{t-i}, \qquad k = 1,2,\dots,H, \tag{2}$$

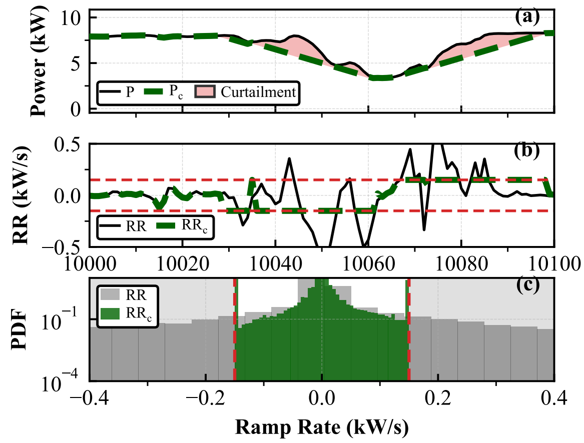

Fig. 4: FAPC Control (a) Power (b) RampRate (c) Probability distribution of daily ramp-rate control

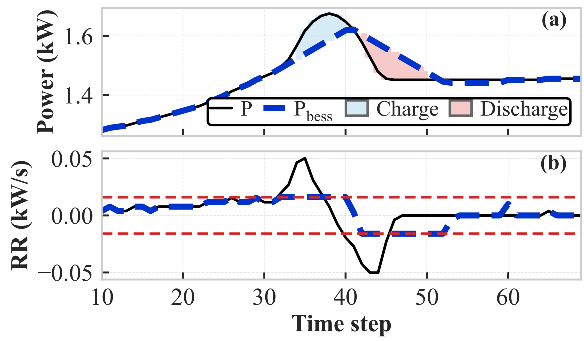

Fig. 5: BESS PRRC control: (a) power and (b) RR profile.

2.2 BESS

Unlike FAPC, the BESS approach smooths power output by compensating fluctuations via controlled charging and discharging [2,6]. Fig. 5 depicts an example of power output and RR profiles under BESS operation. While BESS can significantly reduce RR violations without throwing away energy, its effectiveness is limited by storage capacity, and state-of-charge constraints. This means that insufficient storage capacity may still lead to violations. Fig. 6 illustrates the BESS control flowchart, which adopts a slow-charging strategy and enforces curtailment when storage constraints are reached.

2.3 PRRC Evaluations Metrics

Throughout the literature, various metrics have been employed to evaluate PRRC performance. First, the total curtailed energy due to the PRRC is computed as:

$$\text{Curtailment} = \int |P - P_c|\, dt. \tag{3}$$

which captures the energy loss induced by curtailment, which may be significant particularly in the forecasting-based approach.

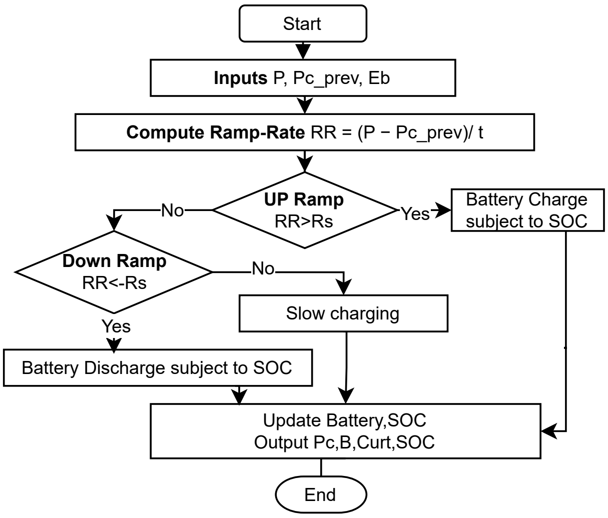

Fig. 6: Flowchart of the BESS PRRC strategy.

Second, the Number of Violations (N_{viol}) is defined by counting the number of instances in which the ramp rate (RR_i) exceeds the allowable limit R_s in either direction:

$$N_{\text{viol}} = \sum_{i=1}^{n} \Big[(RR_i > R_s) \vee (RR_i < -R_s) \Big]. \tag{4}$$

While these metrics assess the PRRC performance, they do not reflect the negative impact caused to the grid from the system operator's perspective. This paper introduces, in the following section, the concept of Violation Energy to quantify that impact.

3 Cost of violations

3.1 Violation Energy

The main premise of this paper is that system operators have ramping flexibility at their disposal to counterbalance excessive solar generation variability, whose cost can be used to quantify the economic impact of RR violations. In other words, the excess solar energy during RR overshoots can be mitigated via reducing generation from other sources (down-ramp capability), while energy shortfall during steep RR drops can be counterbalanced by ramping up other resources in the network (up-ramping capability). With this assumption, calculating the excess/shortfall energy during violations and pricing it at the ramping flexibility rate (e.g. from [8]) allows for a solid and transparent penalty mechanism. To this end, this paper introduces the *Violation Energy* metric E_{viol} to do just that:

$$E_{\text{viol}} = E^{\uparrow}_{\text{viol}} + E^{\downarrow}_{\text{viol}} \tag{5}$$

$$E^{\uparrow}_{\text{viol}} = \int\!\!\int [\max(RR, R_s) - R_s]\, dt\, dt \tag{6}$$

$$E^{\downarrow}_{\text{viol}} = \int\!\!\int [\max(-RR, R_s) - R_s]\, dt\, dt \tag{7}$$

Where $E_{\text{viol}\uparrow}$ and $E_{\text{viol}\downarrow}$ indicate the energy during up- and down- violations respectively - see Fig. 7. The shaded region

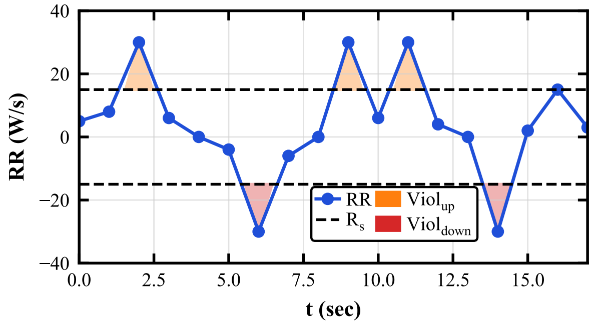

Fig. 7: Ramp-rate violations and Violation energy.

corresponds to the area where *RR* exceeds the threshold *Rs*; this excess above the limits is integrated twice over time to obtain the violation energy defined in (6)–(7). It is important to differentiate between the two, as up-ramping flexibility is much costlier than down-ramping [8]. This formulation enables a physically meaningful and economically relevant quantification of violation, which is later incorporated into the LCOE analysis as well.

3.2 Violation Levelized Cost of Electricity (VLCOE)

The levelized cost of electricity (LCOE) is widely used to evaluate the economic performance of power generation systems. Although the standard LCOE formulation accounts for curtailments, there is no study to consider the economic cost of violations. This paper fills this gap by reformulating LCOE to the Violation Levelized Cost of Electricity *(VLCOE)* as:

$$\text{VLCOE} = \left(\sum_{y=1}^{n} \frac{I_y + OM_y + C_{\text{viol},y}}{(1+d)^y} \right) \Big/ \left(\sum_{y=1}^{n} \frac{E_y}{(1+d)^y} \right) \tag{8}$$

Where I_y denotes the investment cost in year y (the initial installation cost in $y = 1$), OM_y is the annual operation and maintenance cost in year y as percentage, E_y is the energy generated in year y, $C_{\text{viol},y} = c^{\uparrow}_{\text{viol}} E^{\uparrow}_{\text{viol},y} + c^{\downarrow}_{\text{viol}} E^{\downarrow}_{\text{viol},y}$ accounts for violation energy costs, d is the discount rate, and n is the project lifetime in years. By integrating E_{viol} into the LCOE framework, VLCOE enables for the first time accounting for additional investment,reduced yield from curtailments and penalties from unresolved violations for a fair comparison among FAPC and BESS smoothing alternatives.

4 Implementation and Results

4.1 Dataset

To evaluate the applicability of the work, high-resolution global horizontal irradiance (GHI) data were employed from the Oahu NREL dataset [9]. This 1-year, second-resolution data is converted to power using a dynamic 10kW Simulink photovoltaic (PV) model to run simulations for the different PRRC methods [10]. This model corresponds to the typical two-stage PV system and captures all relevant hardware, control and irradiance-driven dynamics. $RR = \frac{dP}{dt}$, as defined in [1].

Fig. 8 presents three representative days characterised by varying levels of power stochasticity: (a) low, (b) moderate, and (c) high. In high-stochasticity scenarios, the frequency of ramp events increases, leading to more violations. This trend is evident in (d), which illustrates the RR profiles for each day.

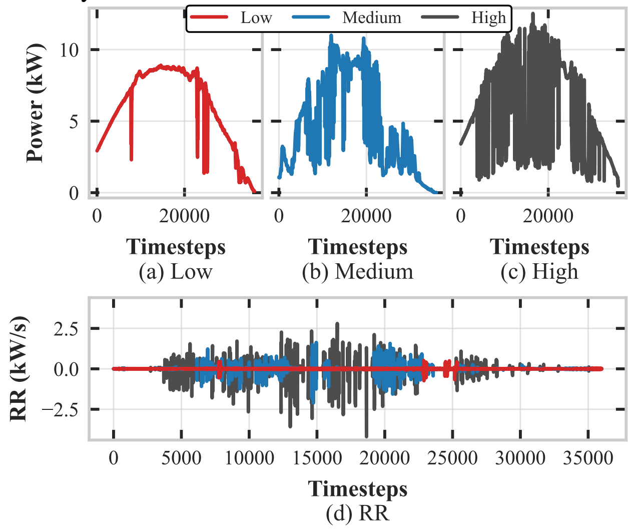

Fig. 8: Power and RR profiles for different variability days.

4.2 System parameters and costs

RR limits (Rs) recommended by operators usually range between 5–20% / min, with 10% / min being the most common value and treated here as the benchmark threshold [11]. For the case study 10 kW system, this corresponds to $Rs \approx$ 16 W/s. Although such RR limits are typically applied to large-scale power plants, there is growing pressure for application to lower capacities. The following analysis explores whether a rooftop kW-level PV system could adhere to such stringent limits and at what cost.

Table 2 gives the system specifications and costs. The penalty costs are derived from the flexible ramp product (FRP) framework for the MISO electricity market proposed by Cornelius et al. [8]. It is worth noting that the downward penalty (i.e. cost of up-ramping flexibility) is much higher than upward penalty (i.e. cost of down-ramping), reflecting system economics by which sharp generation increases are harder than drops.

4.3 Evaluation and Sensitivity Analysis

This section presents a techno-economic assessment of the proposed PRRC strategies. Table 3 summarises the performance and cost metrics for the original case (i.e. no PRRC applied), BESS-based strategies with capacities ranging from 0.1–5 kWh, and the two FAPC variants. The FAPC strategy employs a Perfect Forecaster (PF) with a horizon of $H = 550$ time steps, achieving zero violations. A baseline persistence model (Prs) with identical lag and horizon settings is also included for comparison.

Table 2: System specifications, costs, and penalties

Parameter	**Value**
System specifications	
Number of years (n)	25
Discount rate (d) [6]	0.04
Operating Maintenance (OM_y) [6]	0.035
PV capacity	10 kW
# Battery replacements	4
Costs and penalties	
PV cost (1.49/W)[2]	1490 USD/kW
BESS cost (0-8 kwh) [12]	1159 USD/kWh
Installation Battery Cost [13]	1000 USD
Upward penalty[8]	0.5 USD/kWh
Downward penalty[8]	3.5 USD/kWh

The original uncontrolled case features thousands of violations that incur over $1,000 in penalties per year, thus yielding a VLCOE of more than 15 c/kWh. With the inclusion of BESS, even very small capacities reduce the number and energy of violations resulting in reductions in VLCOE by about 30% in many cases. Interestingly, the FAPC alternatives deliver quite descent performance as well, with the non-ideal (benchmark) PF achieving the lowest VLCOE among all methods, while the practical (but naive) Prs yielding a VLCOE of less than 12 c/kWh.

A sensitivity analysis on the battery size follows in Fig. 9 for different Rs values. Expectedly, larger BESS capacities entail less curtailment, fewer violations and less violation energy for all R_s values in Fig. 9(a)–(c), but the VLCOE in Fig. 9(d) does not follow the same monotonic trend as it accounts for the investment cost. Fig. 9(d) maps the optimal battery size for various Rs values, a relation that seems to be sufficiently represented by a second-order polynomial:

$$C_{\text{opt}}(R_s) = 1.287 \times 10^{-4} R_s^2 - 1.242 \times 10^{-2} R_s + 0.4535 \quad (9)$$

This relation could be used as a guide for sizing BESS in PRRC applications.

5 Conclusions

This paper introduces the concept of violation energy and quantifies its associated penalty cost on PRRC strategies using the VLCOE metric. The results show that the FPAC methods hold great potential, with the ideal/perfect benchmark achieving the best value, but even simple/naive forecaster delivering much better than no ramp-rate control at all. The BESS options proves the best practical approach, with very small batteries effectively quashing violations. The analysis concludes with a formula for the optimal battery size depending on the RR threshold applied.

Future work involves exploring more advanced nowcasting techniques that could potentially beat the BESS alternatives.

Table 3: Performance and violation metrics of the different models (Rs 16 W/s).

Model	**Annual Energy (kWh)**	**Curt. (kWh/yr)**	Viol_{up}	$\text{Viol}_{\text{down}}$	E_{up} (kWh)	E_{down} (kWh)	$\text{Eviol}_{\text{cost}}$ (\$/yr)	VLCOE (\$/kWh)
Original	18,100	0	1,738,095	1,546,992	312.6	315.6	1,261	0.1512
B0.1	16,711	1,389	0	17,994	0	13.3	46	0.1084
B0.2	17,129	971	0	9,507	0	7.6	27	0.1064
B0.3	17,367	733	0	6,577	0	5.4	19	**0.1062**
B0.4	17,522	578	0	4,652	0	3.8	13	0.1066
B0.5	17,638	462	0	3,429	0	2.9	10	0.1075
B1	17,896	204	0	899	0	0.8	2.8	0.1139
B3	18,034	67	0	24	0	0.017	0.06	0.1463
B5	**18,063**	**38**	0	**2**	0	**0.004**	**0.01**	0.1793
PF	14,559	3,541	0	0	0	0	0	**0.1013**
Prs	15,439	2,541	0	652,132	0	75.9	266	0.1128

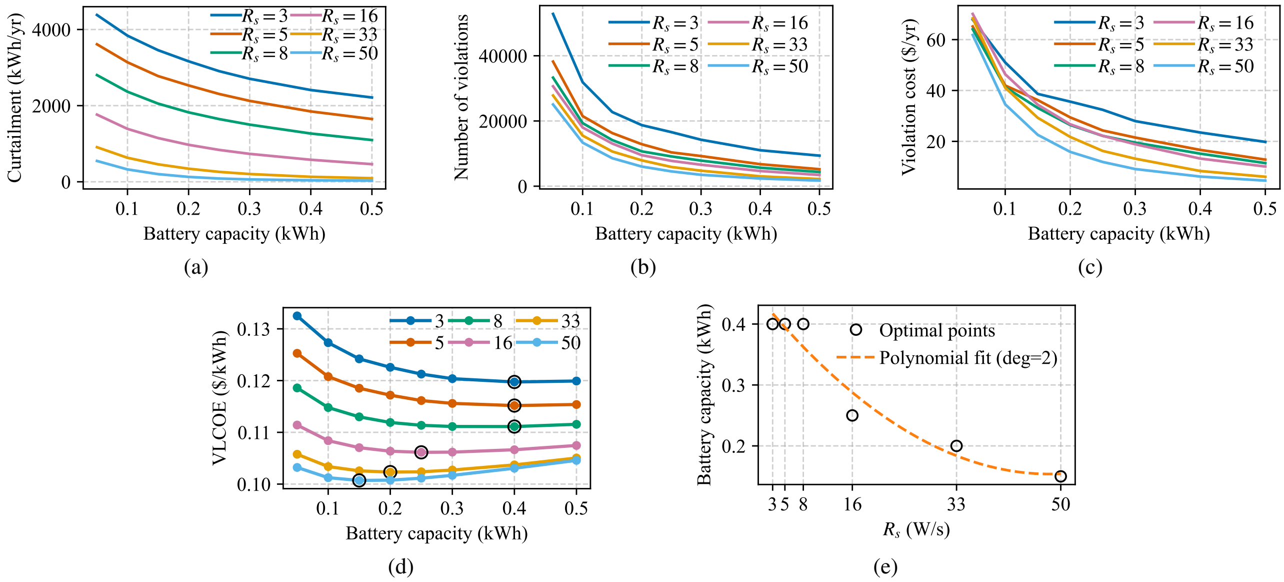

Fig. 9: Effect of Rs on (a) curtailment, (b) number of violations, (c) violation cost, (d) VLCOE , and (e) optimal capacity.

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