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Economic Value of Intraday Photovoltaic Power Forecast Updates for Energy Storage Dispatch in Grid-Connected Microgrids

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Abstract: Grid-connected photovoltaic (PV) microgrids coordinate battery dispatch with grid purchases, and forecast errors can trigger costly emergency energy. This study evaluates a common 10-minute linear-programming model over 334 days in 2025, separating forecast source, rolling control, and added intraday releases under the stated settlement rules. Under the fixed tariff, replacing the historical seven-day mean with the official 00:00 forecast raises static cost by RMB 352,530.85; rolling control under the same forecast adds RMB 2,108.15. Adding the 06:00, 12:00, and 18:00 releases to the same rolling controller lowers cost by RMB 972,910.20 versus the 00:00-only case (6.58%) and cuts emergency energy by 50.48%. The broader S1-to-S6 reduction of RMB 618,271.20 includes all three contrasts. Across 334 paired dates, mean S1-S6 savings are RMB 1,851.11/day (95% bootstrap CI: RMB 1,320.73-2,414.82), with 71.95% from the highest-saving decile. Variable-tariff results show the same direction under a separate matched baseline. Sensitivities and data limits constrain investment claims.

Keywords: Photovoltaic microgrid, economic dispatch, state-of-charge dynamics, rolling model predictive control, forecast-release value.

1. Introduction

Grid-connected photovoltaic microgrids coordinate local solar generation, demand, battery storage, and grid purchases. Forecast errors change procurement and emergency settlement; the value of updated information therefore depends on when forecasts arrive and how deviations are settled. In each ten-minute interval, a day-ahead purchase plan must balance expected demand and PV output with the battery's state of charge and power limits. After delivery begins, completed intervals are fixed, while later forecast releases can affect only the remaining schedule. Thus, forecast value depends jointly on forecast quality, release time, storage flexibility, and the settlement rule for deviations.

Related work examines economic model predictive control and staged market dispatch [1, 2], probabilistic and scenario-based PV-storage scheduling [3–5], long-horizon correction and robust day-ahead/intraday control [6, 7], intraday PV forecasting and correction [8, 9], and degradation-aware scheduling [10]. These studies provide methods for managing uncertainty, linking forecasts to dispatch, and accounting for storage use. However, results across separate studies are difficult to compare when forecast information, control rules, storage boundaries, or settlement multipliers differ. Such differences may obscure whether measured savings come from the forecast source, the controller, or the timing of new information.

To separate these effects, this study evaluates the forecast source, rolling controller, and added intraday releases under a shared 10-minute operating grid, battery model, and settlement structure. The analysis first compares the historical seven-day mean with the official 00:00 forecast, then measures rolling-control cost under the same forecast source, and finally compares a 00:00-only schedule with schedules that also use 06:00, 12:00, and 18:00 updates. Paired daily outcomes and bootstrap intervals summarize fixed-tariff differences; a separate variable-tariff analysis and sensitivity checks examine whether the pattern persists under observed prices and stated assumptions. This operational design isolates the incremental value of forecast releases without treating it as an investment valuation. Forecast accuracy alone does not capture the value of acting before an interval is settled.

2. System Data and Dispatch Model

The operating horizon is divided into 144 ten-minute intervals per day. Power values are converted to interval energy using a one-sixth-hour step. The system comprises a community load, PV generation, a battery, and a connection to the external grid. PV is used locally before grid purchases; any remaining surplus is curtailed because export revenue is not modeled. Emergency procurement supplies any residual deficit and is settled at five times the ordinary tariff.

The battery has a nominal capacity of 12,000 kWh, a state-of-charge range of 1,200-10,800 kWh, and a maximum charge and discharge power of 5,000 kW. Charge and discharge each use an efficiency of 0.9, so the round-trip efficiency is 0.81. The representative-day case imposes a cyclic terminal state but lets the common start/end value be selected by the optimization. In the annual cases, each day starts and ends at 6,000 kWh; the daily reset means that inter-day state transfer is not evaluated. Table 1 lists the shared operating parameters.

Table 1. Shared storage and dispatch parameters.

Parameter	Value	Parameter	Value
Time step	10 min	Intervals per day	144
Nominal energy capacity	12,000 kWh	Usable SOC range	1,200-10,800 kWh
Charge/discharge power limit	5,000 kW	One-way efficiency	0.9 / 0.9
Round-trip efficiency	0.81	Emergency purchase price	5 x ordinary tariff
Representative-day SOC boundary	Cyclic; optimized at 8,550 kWh	Annual daily SOC boundary	6,000 kWh at start/end

For each interval, grid purchases, PV generation, and battery discharge supply the community load, battery charging, and any curtailed PV. Here, q_t denotes purchased interval energy (kWh); P_t^pv and L_t denote PV and load power (kW); u_t^c and u_t^d denote charge and discharge power at the bus-side ports (kW); E_t is stored energy (kWh); and w_t >= 0 denotes curtailed PV energy (kWh). With Δt = 1/6 h, every power term in the balance is converted to interval energy. Battery energy increases by the efficient part of charging and decreases by the internal energy required for discharge. The objective minimizes purchased electricity cost. Under positive purchase prices and no other cycling incentive, simultaneous charging and discharging is dominated by round-trip losses; the representative-day optimum contains no such simultaneous action.

$$\min_{q,u_t^c,u_t^d} C = \sum_{t=1}^{144} c_t q_t \tag{1}$$

$$q_t + P_t^{pv}\Delta t + u_t^d \Delta t = L_t \Delta t + u_t^c \Delta t + w_t \tag{2}$$

$$E_{t+1} = E_t + \eta u_t^c \Delta t - \frac{u_t^d \Delta t}{\eta} \tag{3}$$

$$E_{\min} \le E_t \le E_{\max} \tag{4}$$

$$0 \le u_t^c \le P_{\max}, 0 \le u_t^d \le P_{\max}, q_t \ge 0 \tag{5}$$

2.1. Forecast and Settlement Structures

The static annual case uses actual load and a PV forecast equal to the mean of the preceding seven days at the same time. The planned battery and grid schedule remain fixed during execution; realized PV determines any shortfall, with emergency energy charged at five times the time-of-use tariff. Forecast error therefore affects cost when planned supply and available storage cannot cover realized demand.

$$C_{\text{real}} = C_{\text{plan}} + C_{\text{emergency}} \tag{6}$$

$$C_{\text{emergency}} = 5 \sum_{d,t} c_t e_{d,t} \tag{7}$$

The rolling controller linearly interpolates hourly PV forecasts to the ten-minute grid and updates at 00:00, 06:00, 12:00, and 18:00. Executed intervals stay fixed while the remaining horizon is re-optimized; future realized PV is not used. Upward revisions are charged at 1.5 times the ordinary tariff and downward revisions are refunded at 0.5 times that tariff. State of charge returns to 6,000 kWh at day's end.

$$a_t = c_t(1.5\Delta q_t^+ - 0.5\Delta q_t^-) \tag{8}$$

Under the observed variable tariff, the mean price is RMB 0.7575/kWh (SD 0.3361; range 0.0076-1.7936), with the same battery and settlement model. The fixed-tariff matrix varies forecast source and control across six cases. S5 uses the rolling controller with only the official 00:00 forecast; S6 adds the 06:00, 12:00, and 18:00 releases. S5–S6 serve as the matched operational comparison for added releases.

2.2. Operational Information Reference

An operational realized-cost reference based on the observed PV trajectory costs RMB 12,245,046.92, compared with RMB 14,420,386.79 for static S1. The resulting realized-cost capture fraction is 28.42%; it is not a classical stochastic-program EVPI or VSS estimate.

3. Results

3.1. Representative-Day Dispatch

The 334-day sample spans seasonal variation in community load, PV output, and variable tariffs. Figure 1 summarizes their intraday and seasonal distributions; it describes the evaluated data and does not identify a dispatch effect.

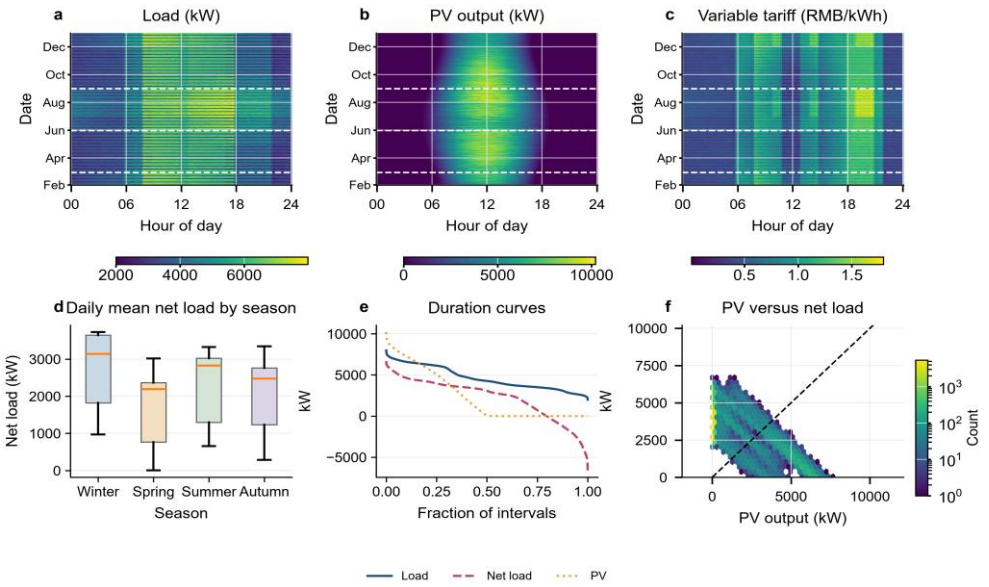


Figure 1. Load, photovoltaic output, and variable tariffs over the 334-day evaluation period.

For the representative day, the linear program yields a purchase cost of RMB 35,118.60 for 59,482.70 kWh, with zero emergency purchases. The cyclic solution starts and ends at 8,550 kWh and shifts grid purchases and battery dispatch across the tariff profile, as shown in Figure 2.

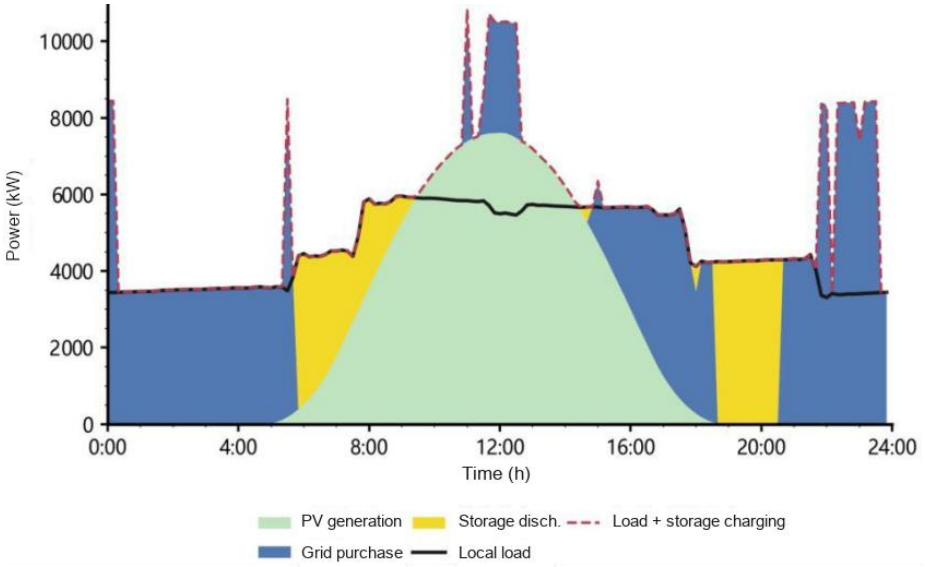


Figure 2. Representative-day grid purchases, PV use, charging, and discharging.

3.2. Historical-Forecast Two-Stage Dispatch

In the 334-day fixed-tariff cases, static S1 using the seven-day same-time mean costs RMB 14,420,386.79. Using the official 00:00 forecast raises static cost to RMB 14,772,917.63 for S2, a forecast-source difference of RMB 352,530.85. S3 uses the same frozen plan as S2, so their costs and emergency outcomes are identical. Table 2 summarizes all six fixed-tariff cases.

3.3. Rolling Forecast Updates and Information Value

Four-release rolling S6 costs RMB 13,802,115.59 over the same 334 days, with 298,154.53 kWh of emergency energy. Compared with S5, which uses the same rolling controller with only the official 00:00 forecast, the added 06:00, 12:00, and 18:00 releases lower cost by RMB 972,910.20 and emergency energy by 303,951.54 kWh (50.48%). This matched-controller difference is the operational estimate for added releases under the stated rules.

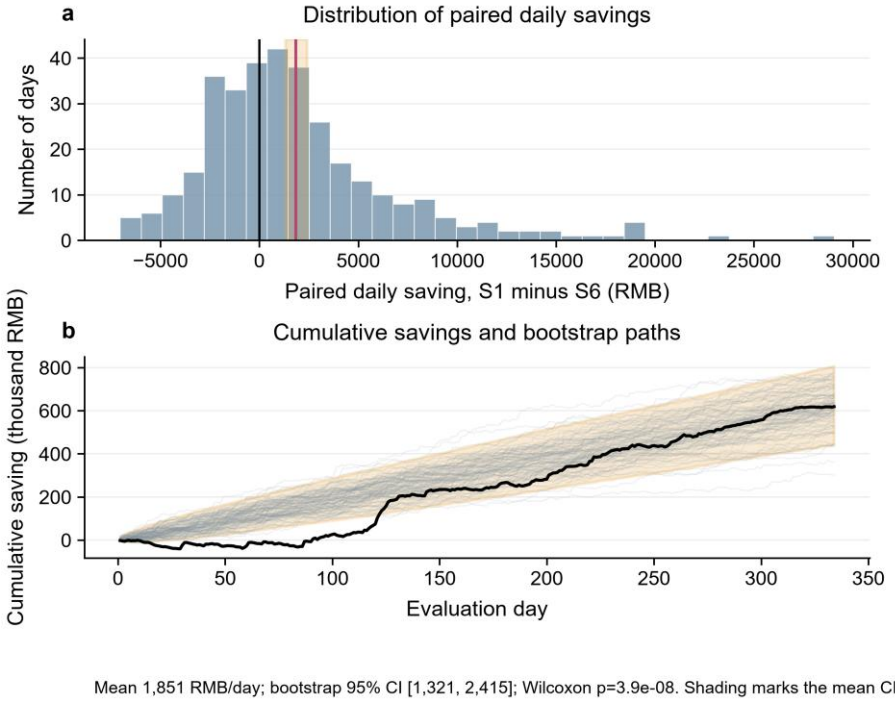


Figure 3. S1-S6 paired daily savings and cumulative bootstrap paths.

The S1-to-S6 reduction of RMB 618,271.20 combines forecast-source, rolling-control, and release contrasts and cannot be attributed solely to updates. Across 334 paired dates, S6 is cheaper on 201 days and more expensive on 133; mean S1-S6 saving is RMB 1,851.11/day (95% bootstrap CI: RMB 1,320.73-2,414.82; Wilcoxon p = 3.92e-08), and the highest-saving decile contributes 71.95%. These statistics compare S1 with S6, not S5 with S6. In Figure 3, panel (a) shading marks the bootstrap interval for mean daily saving; panel (b) shows the spread of cumulative bootstrap paths, not a confidence

interval for the mean.

$$V_{\text{info}} = C_{\text{MPC},00} - C_{\text{MPC,updates}} \quad (9)$$

Forecast-error diagnostics are descriptive. Exact zero errors occur in 42.2% of intervals, and 99.8% of these intervals have zero measured PV output. Figure 4 shows normalized nonzero errors alongside seasonal and Q-Q diagnostics; the tested distributions do not support normal or Laplace error assumptions.

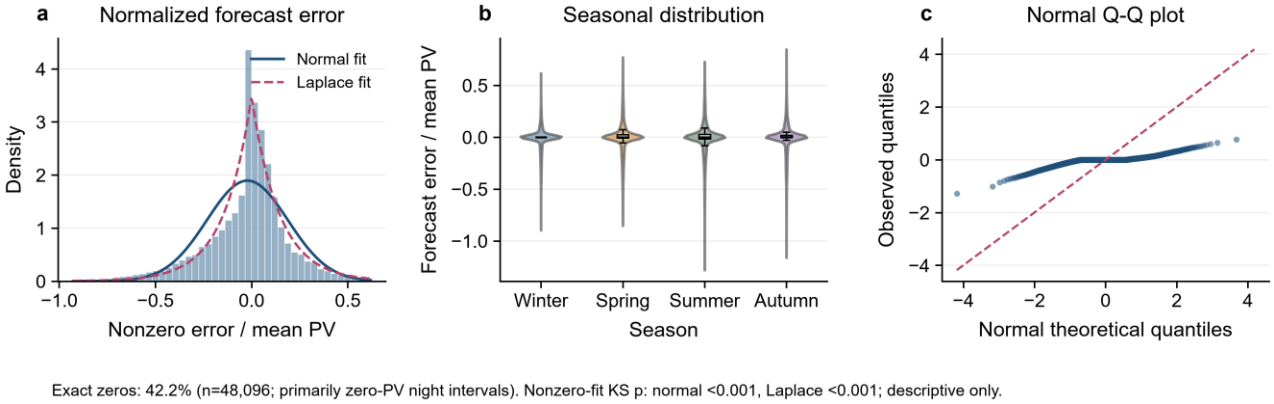


Figure 4. Normalized PV forecast-error distribution and seasonal diagnostics.

Figure 5 compares measured and forecast PV output by season. Forecast windows from different release times can reuse the same realized intervals, so the plotted points are not independent unique times. Seasonal aggregation also masks release- and lead-time differences; high R-squared values alone do not establish dispatch value.

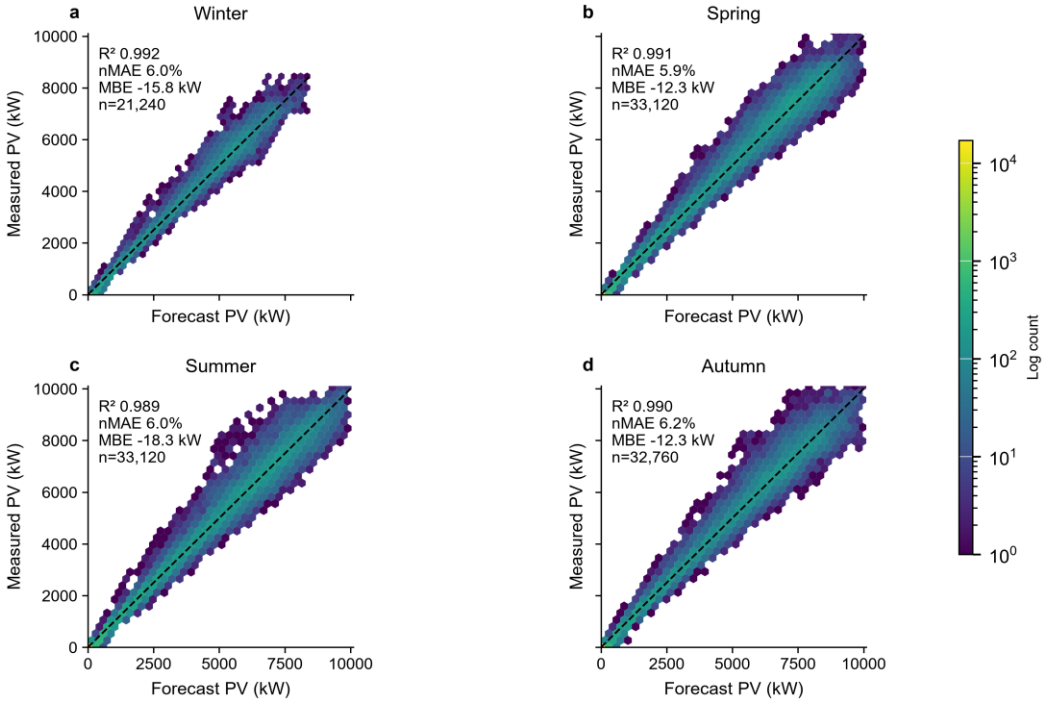


Figure 5. Measured versus forecast PV output by season and release time.

3.4. Variable-Tariff Cases

Under the variable tariff, static Q4-2 costs RMB 15,096,898.49, with 553,424.52 kWh of emergency energy and 12,780,596.24 kWh of throughput. Four-release Q4-3 costs RMB 14,423,918.27, with 297,771.89 kWh of emergency energy and 12,853,705.50 kWh of throughput. Relative to the matched no-new-release rolling baseline Q4-3-S5 (RMB 15,422,368.53), Q4-3 saves RMB 998,450.26. These variable-tariff cases use a separate baseline from S1-S6.

Table 2. Fixed-tariff results for the six attribution cases. The final column shows the relevant cost contrast and its baseline.

Case / policy	Total cost (RMB)	Emergency energy (kWh)	Battery throughput (kWh)	Relevant cost difference (RMB)
S1: 7-day mean, static	14,420,386.79	553,424.52	12,255,496.54	Reference
S2: official 00:00, static	14,772,917.63	601,048.83	12,362,031.71	+352,530.85 vs S1
S3: official 00:00, frozen	14,772,917.63	601,048.83	12,362,031.71	Same as S2
S4: 7-day mean, rolling	14,422,891.62	554,575.94	12,279,430.92	—
S5: official 00:00, rolling	14,775,025.79	602,106.07	12,419,591.94	+2,108.15 vs S2
S6: four releases, rolling	13,802,115.59	298,154.53	12,323,531.19	-972,910.20 vs S5

The S1-to-S6 total gap includes forecast-source and rolling-control changes; only S5-to-S6 estimates the added-release contrast under the same rolling controller. Variable-tariff information value is Q4-3-S5 minus Q4-3.

4. Storage Sensitivity and Model Limitations

The representative-day capacity-power sweep shows diminishing operating-cost reductions at larger ratings, but the model omits capital cost, battery lifetime, replacement, and discounting, so it does not identify an economic optimum or investment return. Sensitivity tests show that cost differences change with efficiency and settlement multipliers; the linear wear-charge test remains favorable through RMB 0.30 per discharged kWh but is not a profitability analysis. In stress cases, state of charge reaches the 1,200-kWh floor; because the model has no load-shedding variable, emergency purchases are not unserved load. Results also depend on known load, point forecasts, daily state resets, and the absence of export revenue.

5. Conclusion

Using a common 10-minute model and stated settlement rules, this study evaluated the value of intraday PV forecast releases for battery dispatch in a grid-connected microgrid. Over 334 days, adding 06:00, 12:00, and 18:00 releases reduced fixed-tariff cost by RMB 972,910.20 (6.58%) and emergency energy by 50.48% compared with matched S5. The broader S1–S6 reduction of RMB 618,271.20 also includes forecast-source and control effects. Under the variable tariff, Q4-3 saved RMB 998,450.26 relative to matched Q4-3-S5. These are operational results under the evaluated data and rules; they do not establish investment returns or classical EVPI/VSS.

Several limitations suggest future research. The study covers one year and one microgrid and assumes known load; multi-year, multi-site validation with uncertain load and PV forecasts is needed to assess robustness. Daily state-of-charge resets exclude interday energy shifting, which multiday optimization with realistic boundary conditions should quantify. Because export revenue is omitted, future models should include market-specific export compensation and curtailment rules. Alternative settlement schemes and probabilistic forecasts could test whether update value persists under other market conditions. The model also excludes battery degradation, replacement, capital cost, and discounting; integrating cycle-dependent aging and lifecycle costs is necessary before assessing economic optimality or investment.

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