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Asymmetric Rolling Dispatch of PV-Storage Microgrids Based on Risk-Quantile Calibration and Sequential Information Updating

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Abstract: PV-storage microgrids with high photovoltaic penetration must maintain supply reliability while limiting procurement costs under uncertain generation, demand, and electricity prices. This study examines how day-ahead grid purchases can be coordinated with risk control, sequential PV forecast updates, and real-time prices. A linear-programming dispatch framework is formulated from the microgrid power balance and battery-state constraints. The emergency-purchase penalty is used to derive an optimal plan coverage probability of 80%; a 31-day window of genuine out-of-sample residuals then calibrates risk-adjusted net load, while the remaining horizon is updated at 00:00, 06:00, 12:00, and 18:00. In a 334-day simulation in 2025, the full-node rolling strategy reduced total procurement cost under fixed time-of-use tariffs from CNY 17.1064 million to CNY 14.9067 million, a 12.86% decrease, and cut emergency energy by 96.47%. Under real-time fluctuating prices, total cost fell from CNY 17.6382 million to CNY 15.4677 million, a 12.31% decrease, while empirical risk coverage was 81.08%. The results show that quantile calibration and causal rolling dispatch can reduce emergency purchases and improve the economic operation of PV-storage microgrids without changing their physical constraints.

Keywords: PV-storage microgrid, Risk quantile, Sequential forecasting, Rolling dispatch, Linear programming, Real-time electricity price.

1. Introduction

Grid-connected microgrids combine local photovoltaic (PV) generation, electrical storage, controllable conversion equipment, and end-use demand. Their value depends on using renewable generation locally while maintaining a reliable connection to the distribution grid. A day-ahead purchase plan can exploit tariff differences by charging storage during low-cost or PV-surplus intervals and discharging during expensive periods. The same plan can become inadequate when weather-dependent PV output, household demand, and electricity prices change after the planning decision. Unserved demand must then be covered through additional grid purchases, which can be substantially more expensive than scheduled energy.

The dispatch decision therefore links several time scales. Day-ahead scheduling needs a defensible reserve against forecast error; intraday operation must respect the measured state of charge and the actual power balance; and each new PV forecast can improve the remaining schedule while also creating settlement costs when a committed purchase is reduced or increased. High-frequency price variation further changes the relative value of charging and discharging across intervals. A single deterministic schedule cannot represent these linked effects, while an unconstrained update can disregard the physical battery state or the asymmetric cost of changing a purchase plan.

Recent studies model microgrid forecast errors with probabilistic methods, develop machine-learning-based forecasts for renewable-energy microgrids, and examine PV and EV forecast impacts on microgrid operation [1-3]. Robust and distributed scheduling methods address renewable and load uncertainty across day-ahead and intraday horizons, including forecast-error-aware energy management [4-6]. Other work integrates probabilistic PV forecasts into stochastic model-predictive control and evaluates storage scheduling under variable weather and prices, battery degradation, and PEV integration [7-10].

This study formulates the framework for 10-minute operating intervals using 2025 microgrid records. The battery power balance and state transition define a linear dispatch model. A fivefold emergency-purchase price is mapped analytically to an 80th-percentile net-load target; a 31-day weighted residual window calibrates that target without using future observations. Forecasts released at 00:00, 06:00, 12:00, and 18:00 update only the unexecuted horizon, with the measured battery state anchoring each re-optimization. The study then compares fixed time-of-use and real-time fluctuating tariffs, including the stated 0.50 and 1.50 price multipliers for reductions and increases in scheduled purchases. This structure evaluates cost, emergency energy, risk coverage, and the economic contribution of sequential information updates within the same physical operating constraints.

2. Microgrid Framework and Operating Data

2.1. Related Foundations and Study Scope

Building on recent work on forecast-error-aware scheduling and storage management [4, 6, 8], the present study examines the operational link between the emergency-purchase penalty and the day-ahead reserve quantile. Under a fixed fivefold penalty, the marginal cost condition yields an 80th-percentile net-load target. Historical out-of-sample residuals calibrate the forecast correction, and sequential updates apply only to the unexecuted horizon, anchored by measured battery state. The method is evaluated under time-

of-use and fluctuating tariffs while retaining common physical constraints.

2.2. System Representation and Constraints

The daily horizon is divided into 144 equal intervals of 10 minutes. Grid purchases, PV energy, fixed demand, battery charging and discharging, and curtailed PV are coordinated at each interval. The battery begins and ends the daily plan at 6,000 kWh, remains between 1,200 and 10,800 kWh, and is limited to 5,000 kW of charge or discharge power. Both charge and discharge efficiencies are 0.90. Grid export is excluded, and any curtailed energy is bounded by available PV generation. These assumptions define the common feasible region for day-ahead, intraday, and fluctuating-price schedules. The operating values are summarized in Table 1.

Table 1. Core operating parameters

Parameter	Value	Operating role
Time resolution	10 min; 144 intervals/day	Decision and balance interval
Battery energy	1,200-10,800 kWh	Allowed stored-energy range
Initial/end-of-day energy	6,000 kWh	Daily cycle anchor
Maximum charge/discharge	5,000 kW	Converter power limit
Charge/discharge efficiency	0.90 / 0.90	Energy-state transition
History window	31 days	Risk-residual calibration
Time decay / weekday gain	14 days / 1.25	Historical sample weights
Emergency purchase price	5 times tariff	Reliability penalty

Let grid purchase, PV generation, demand, battery charge, battery discharge, and curtailed PV denote the interval energy quantities. The balance and state-transition equations are formulated as follows:

$$g_t + p_t^{\mathrm{PV}} + b_t = l_t + c_t^{\mathrm{ch}} + w_t \tag{1}$$

$$s_{t+1} = s_t + \eta_c c_t^{\mathrm{ch}} - \frac{b_t^{\mathrm{dis}}}{\eta_d} \tag{2}$$

Because the objective is cost minimization, tariff values are nonnegative, and both conversion efficiencies are below one, simultaneous charge and discharge only dissipates energy and is excluded at the optimum without binary variables. The physical scheduling core is therefore represented as a linear program.

3. Risk-Quantile Day-Ahead Scheduling

3.1. Emergency-purchase Penalty and the Optimal Quantile

Under fixed time-of-use tariffs, the day-ahead plan is settled at the scheduled tariff, while any uncovered net demand is purchased at five times that tariff. For a single interval with random net demand and planned purchase, the expected procurement cost has the following marginal condition:

$$C(q) = \pi q + 5\pi E[(N-q)^+] \tag{3}$$

$$F(q^*) = 1 - \frac{1}{5} = 0.80 \tag{4}$$

The result follows because the same positive tariff scales both scheduled energy and the emergency penalty; the penalty multiplier determines the coverage probability. The plan should therefore target the 80th percentile of uncertain net demand rather than its mean. This analytical mapping fixes the risk level used in the subsequent forecast calibration.

3.2. Causal Residual Calibration

At midnight, the decision uses only observations through the preceding day. A 31-day rolling history applies exponential time decay with a 14-day scale and a weekday-gain coefficient of 1.25. A weighted local linear trend estimates central net demand. The weighted 80th percentile of genuine one-step out-of-sample residuals then corrects the center forecast. This separates forecast bias from residual risk and avoids using future observations:

$$w_{d,j} = e^{-\Delta_j/14}(1 + 1.25 I_{\mathrm{same,weekday}}), \hat{N}^{0.80} = \overline{N} + Q_{0.80}^{w}(\varepsilon) \tag{5}$$

The day-ahead linear program minimizes scheduled procurement cost subject to the risk-adjusted net-load requirement, battery bounds, state transition, and the 6,000 kWh terminal anchor. Once the day unfolds, measured demand, PV output, and stored energy drive a second linear program. Emergency energy is bounded by the actual uncovered supply deficit, so it cannot be used to charge the battery deliberately. The measured terminal state is passed to the next day.

4. Sequential Forecast Updates and Asymmetric Settlement

The PV forecast is available at 00:00, 06:00, 12:00, and 18:00. Hourly forecasts are linearly interpolated to the 10-minute dispatch grid. At each update, the measured battery state anchors a new optimization of the remaining horizon; executed intervals remain fixed. A recent two-hour measured-load ratio adjusts the remaining load forecast, with the correction decaying as the lead time increases.

Purchase changes are settled asymmetrically. Reducing the original plan incurs a 0.50-tariff penalty on the reduced quantity, while increasing the plan incurs a 1.50-tariff charge on the additional quantity. Let the positive and negative adjustment variables denote power (kW); multiplying them by the 10-minute interval yields energy (kWh) in the linear settlement term:

$$\mathrm{J} = \sum_{\mathrm{t}=1}^{\mathrm{T}} \pi_{\mathrm{t}} \Delta \mathrm{t}(1.50\mathrm{u}_{\mathrm{t}}^{+} - 0.50\mathrm{u}_{\mathrm{t}}^{-}) \tag{6}$$

At execution, a local causal rule charges when scheduled supply exceeds actual net load, discharges when a deficit occurs, and purchases emergency energy only after battery power or energy limits prevent further balancing. The rollout therefore combines forecast adaptation with immediate physical feasibility, rather than revising decisions that have already been executed.

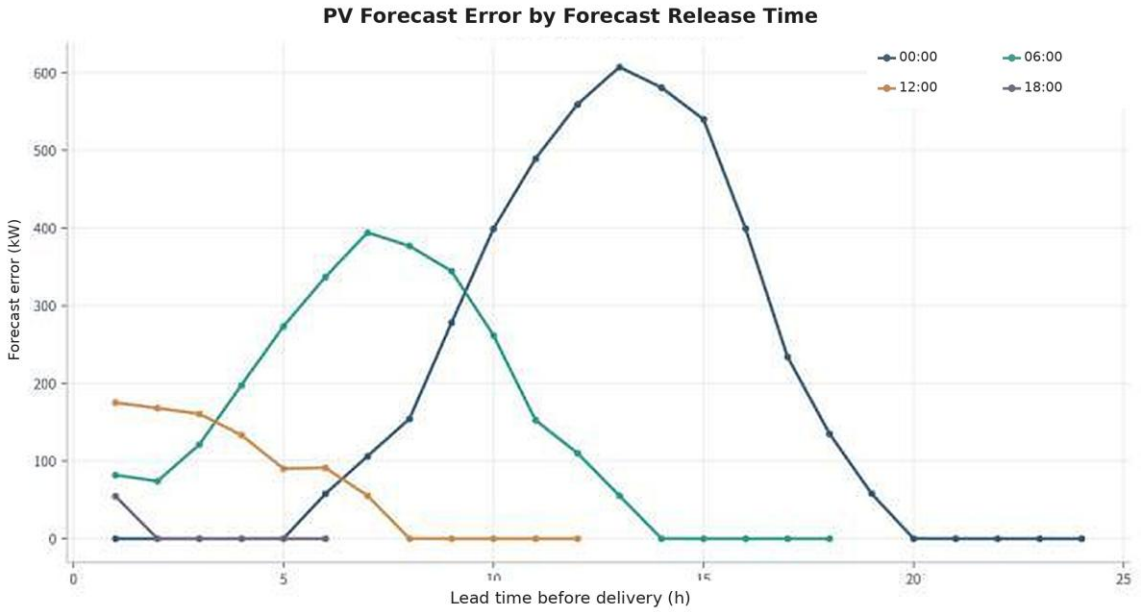


Figure 1. PV forecast error by publication time

Figure 1 shows forecast error decreasing as the publication time approaches delivery. The midnight forecast has an average absolute error of 607.45 kW at the midday PV peak; the maximum errors for forecasts issued at 06:00 and 12:00 are 394.20 kW and 174.60 kW, respectively. This improvement provides the information basis for reducing avoidable plan deviations and emergency purchases.

Table 2. Annual cost and emergency-energy outcomes under sequential forecast updates.

Tariff case	Forecast nodes	Annual cost (CNY 10^4)	Emergency energy (10^4 kWh)	Saving vs. baseline
Fixed time-of-use	00:00 only	1,710.64	41.52	-
Fixed time-of-use	00:00 + 06:00 + 12:00 + 18:00	1,490.67	1.46	219.97; 12.86%
Fluctuating real-time	00:00 only	1,763.82	43.60	-
Fluctuating real-time	00:00 + 06:00 + 12:00 + 18:00	1,546.77	1.60	217.04; 12.31%

Across 334 operating days from 1 February through 31 December 2025, the fixed-tariff risk forecast achieved 81.08% empirical coverage over 48,096 time points; monthly coverage ranged from 78.65% to 84.50%. With all three intraday updates, the fixed-tariff total fell from CNY 17.1064 million to CNY 14.9067 million, while emergency energy declined from 415,200 kWh to 14,600 kWh. The fluctuating-price case reduced annual emergency energy from 436,000 kWh to 16,000 kWh. The reported constraint checks show power-balance residuals on the order of 10^-12, with no battery-bound or simultaneous charge-discharge violations. Table 2 summarizes the annual cost and emergency-energy outcomes for the forecast-update schedules.

5. Rolling Dispatch Under Real-Time Price Fluctuations

The 10-minute tariff data range from CNY 0.01/kWh to CNY 1.79/kWh, with an annual mean of CNY 0.77/kWh. The changing tariff reshapes the relative value of purchases across time and therefore changes the storage arbitrage path. It does not change the risk quantile when the emergency price remains a fixed multiple of the contemporaneous tariff. The common tariff factor cancels from the marginal condition:

$$\pi_t[1 - 5P(N_t > q)] = 0 \Rightarrow F_{N_t}(q^*) = 0.80 \qquad (7)$$

Accordingly, the fluctuating tariff changes the time-dependent objective coefficients but not the 80% risk target. Day-ahead purchases are weighted by the realized time-series tariff, and the remaining horizon is re-optimized at each forecast update using the current stored-energy state. The same asymmetric settlement multipliers are applied using the real-time tariff at each interval. The annual price distribution is shown in Figure 2, while Figure 3 compares the tariff profiles on four representative dates.

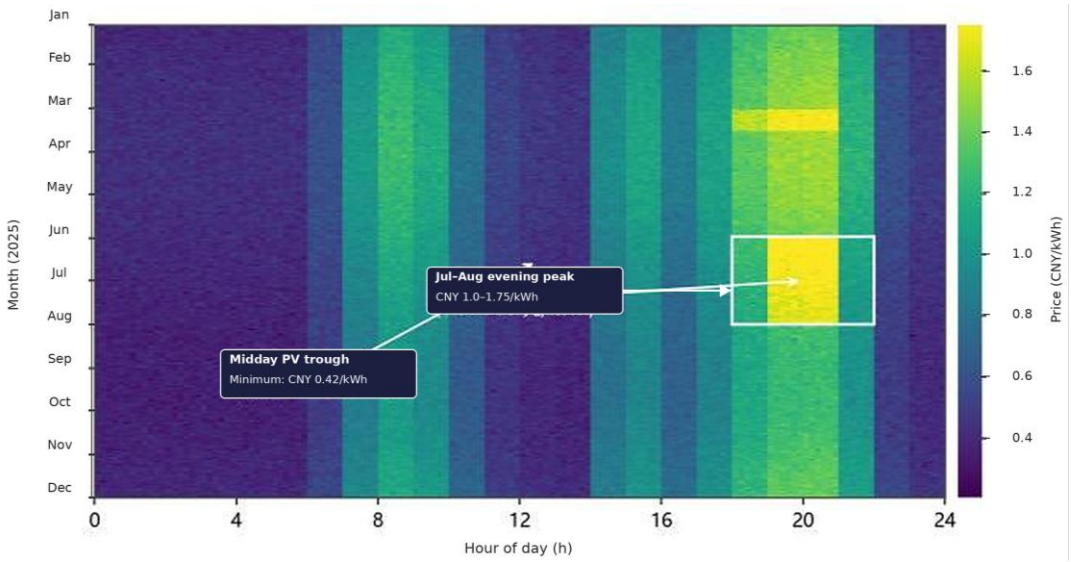


Figure 2. Annual distribution of 10-minute electricity prices

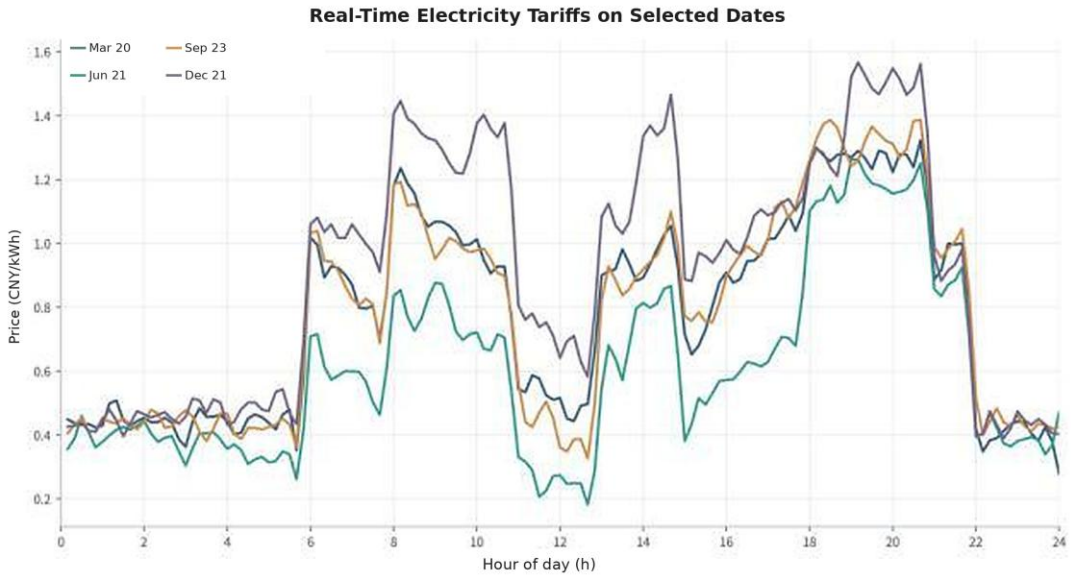


Figure 3. Real-time tariff profiles on four representative dates



Figure 4. Annual procurement cost as additional forecast updates are introduced

The four-node strategy reduced fluctuating-tariff cost from CNY 17.6382 million to CNY 15.4677 million, a CNY 2.1704 million saving or 12.31%. Emergency energy decreased from 436,000 kWh to 16,000 kWh, a 96.33% reduction. Rolling

adjustment also lowered annual cost by CNY 1.0757 million, or 6.50%, relative to the corresponding static day-ahead strategy. Figure 4 displays the monotonic cost decline as the 06:00, 12:00, and 18:00 forecast updates are added.

6. Conclusion

A linear-programming framework was developed for PV-storage microgrid procurement and battery dispatch under deterministic schedules, uncertain net load, sequential PV forecast updates, and high-frequency real-time tariffs. A fivefold emergency-purchase price analytically implies an 80% net-load coverage quantile. The calibrated forecast and receding-horizon implementation preserve the microgrid power balance, battery limits, and measured state of charge at each update.

In the 334-day 2025 simulation, adding all three intraday updates reduced total cost by 12.86% under fixed time-of-use tariffs and by 12.31% under fluctuating tariffs. Emergency energy fell by more than 96% in both comparisons, while empirical risk coverage under the fixed-tariff case remained close to the theoretical target. These findings support the use of calibrated reserve levels and sequential forecast information for economic operation without relaxing supply or storage constraints.

The model uses a recent weighted history and does not explicitly price battery degradation. Future research can add weather-aware load and PV forecasts, adaptive residual windows for seasonal and holiday shifts, and battery-aging costs. Tests across multiple microgrids and full-year operating records could establish transferability and quantify the trade-off among forecast accuracy, battery wear, and procurement savings.

References

[1] Yoo, Y., & Jung, S. (2024). Modeling forecast errors for microgrid operation using Gaussian process regression. Scientific Reports, 14, 2166.

[2] Aguilar, D., Quiñones, J. J., Pineda, L. R., et al. (2024). Optimal scheduling of renewable energy microgrids: A robust multi-objective approach with machine learning-based probabilistic forecasting. Applied Energy, 369, 123548.

[3] Manzolini, G., Fusco, A., Gioffrè, D., et al. (2024). Impact of PV and EV Forecasting in the Operation of a Microgrid. Forecasting, 6(3), 591–615.

[4] Yang, M., Wang, J., Chen, Y., et al. (2024). Data-driven robust optimization scheduling for microgrid day-ahead to intra-day operations based on renewable energy interval prediction. Energy, 313, 134058.

[5] Yin, H., Wang, Y., Wu, G., et al. (2024). Distributed optimal operation of PV-storage-load micro-grid considering renewable and load uncertainties. Journal of Energy Storage, 86, 111168.

[6] Zhang, K., Zou, G., Zhang, J., et al. (2025). Microgrid energy management strategy considering source-load forecast error. International Journal of Electrical Power & Energy Systems, 164, 110372.

[7] Brown, P., & Göl, M. (2026). Bayesian probabilistic photovoltaic power forecasting and stochastic model-predictive control for an agricultural microgrid. Solar Energy, 304, 114197.

[8] Stevenson, A., Riggs, H., & Sarwat, A. I. (2024). Data-driven scheduling of a grid-connected university campus battery energy storage system considering variable weather and energy pricing. Energy Reports, 12, 5116–5132.

[9] Minh, N. Q., Linh, N. D., & Khiem, N. T. (2024). A mixed-integer linear programming model for microgrid optimal scheduling considering BESS degradation and RES uncertainty. Journal of Energy Storage, 104, 114663.

[10] Nawaz, A., Wang, D., Mahmoudi, A., et al. (2025). MPC-driven optimal scheduling of grid-connected microgrid: Cost and degradation minimization with PEVs integration. Electric Power Systems Research, 238, 111173.