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Electricity-Purchase Optimization for PV-Storage Microgrids Based on Historical Error Scenarios and Rolling Correction

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Abstract: This study investigates electricity-purchase optimization for a PV-storage microgrid under changing photovoltaic output, load and prices, with storage coupling adjacent intervals. It establishes a unified ten-minute physical and accounting framework and compares four information settings using deterministic linear programming with an MILP cross-check, historical-error scenario programming, finite-state dynamic programming for rolling correction, and scenario programming under time-varying prices. The deterministic schedule costs 35,126.95 CNY, 26.90% below the no-storage baseline. Over 334 days, the historical-error scenario setting costs 14,731,085.32 CNY. Rolling updates at 06:00, 12:00, and 18:00 reduce cost from 16,143,244.46 to 13,905,968.07 CNY (13.86%) and emergency purchases by 81.55%. Under variable prices, intraday updating cuts emergency purchases by 38.69% but raises total cost slightly (0.06%). These results show that the shared framework supports physically consistent comparisons, rolling feedback can mitigate forecast errors, and price updates should be assessed alongside adjustment costs and storage state.

Keywords: PV-storage microgrid, energy storage scheduling, stochastic optimization, rolling correction, time-varying electricity prices.

1. Introduction

A photovoltaic-storage microgrid must make electricity-purchase decisions while three types of information change at different rates. Load and photovoltaic output are observed or forecast at ten-minute resolution, the storage state couples adjacent intervals, and electricity prices can be known only partially before operation. A schedule that is optimal under complete information can therefore become expensive when forecast errors trigger emergency purchases or when the storage trajectory reaches an operating boundary. Stochastic storage scheduling, model predictive control and scientific-computing tools provide useful foundations for this class of problem [1-3].

The underlying physical system is common across operating settings: ordinary grid purchase, emergency purchase, photovoltaic energy, storage charge and discharge, unused photovoltaic energy and storage state must satisfy a power balance, storage recursion and mutually exclusive charge-discharge logic. What changes is the information boundary. A deterministic day-ahead model assumes the full day is known; a historical-error model represents the unavailable future with paired residual scenarios; a rolling model fixes executed intervals and re-optimizes only the remaining horizon after new forecasts arrive; and a price-scenario model replaces a fixed tariff with a forecast distribution and revises the plan at selected times. Recent research emphasizes that storage sizing, forecast uncertainty and online control should be evaluated together rather than as isolated layers [4-6].

This paper consolidates those settings into one physical and accounting framework. A ten-minute time axis is used throughout, power is converted to energy by the common step length, and the same storage bounds, efficiency definitions and nonnegativity conditions are retained. The solution method follows each setting: linear programming for the deterministic and historical-error layers, finite-state dynamic programming for rolling correction, and scenario linear programming for time-varying prices. Scenario-specific terms are added only where required, allowing direct comparison of cost, emergency energy and storage movement under consistent physical accounting [7-9].

The study uses 144 ten-minute intervals per day, a 12,000 kWh storage device with a 10%-90% operating range, a 5,000 kW charge or discharge limit, and charging and discharging efficiencies of 0.90, corresponding to a round-trip efficiency of 0.81. The evaluation period for uncertain and price scenarios is 334 days from February 1 to December 31, containing 48,096 ten-minute intervals. The reported results quantify the value of storage, historical error scenarios, updates at 06:00, 12:00 and 18:00, and a 14-day same-time price forecast. Related multi-timescale control and energy-trading studies support this focus on information value and rolling decision quality [10-13].

2. Unified Physical and Accounting Framework

2.1. Time Axis, Energy Conversion and Storage State

The day contains T=144 ten-minute intervals. Let d denote the operating day and t the interval index. The planning horizon is represented by interval-boundary storage states E_0,...,E_T. A forecast publication at hour h becomes available at k=6h, so the remaining horizon is expressed on the same grid.

$$T = 144, t = 0, \dots, T-1, \Delta t = \frac{1}{6}, M = 5000\Delta t \quad (1)$$

$$\ell_{\mathrm{d,t}} = \Delta t L_{\mathrm{d,t}}, \varphi_{\mathrm{d,t}} = \Delta t P_{\mathrm{d,t}}^{\mathrm{PV}} \quad (2)$$

Let g_t be ordinary grid purchase, h_t emergency purchase, c_t storage charge, b_t storage discharge and w_t unused photovoltaic energy. The base energy balance is:

$$g_{d,t} + \varphi_{d,t} + b_{d,t} + h_{d,t} = \ell_{d,t} + c_{d,t} + w_{d,t} \quad (3)$$

$$E_{t+1} = E_t + \eta_c c_t - \frac{b_t}{\eta_d}, 1200 \le E_t \le 10800, E_k = e_k, E_T = 6000 \quad (4)$$

An explicit binary representation of mutually exclusive charging and discharging is:

$$0 \le c_t \le M z_t, 0 \le b_t \le M(1 - z_t), z_t \in (0,1) \quad (5)$$

2.2. Objective Functions and Information Extensions

The deterministic cost is the sum of ordinary purchase cost. For uncertain settings, emergency purchase is assigned a fivefold price to represent the operational value of unserved or late-arriving energy. Rolling adjustment terms are added only to the remaining horizon, while price-scenario coefficients replace the fixed tariff without changing the physical constraints.

$$C_{total} = C_{plan} + C_{adj} + C_{emg} \quad (6)$$

The framework therefore has one physical core and four information extensions. The deterministic setting uses full daily inputs and is solved by linear programming with an MILP cross-check; the historical-error setting uses scenario linear programming; the rolling setting uses finite-state dynamic programming after fixing executed intervals; and the price setting uses scenario linear programming with time-varying price coefficients and update times.

3. Full-Information Intraday Scheduling

The full-information setting uses the 144-interval load, photovoltaic power and electricity price as known inputs. The linear-programming formulation minimizes ordinary purchase while the storage state transfers photovoltaic energy from surplus intervals to higher-price or deficit intervals. The continuous LP is cross-checked with a binary MIP representation of charge-discharge exclusivity; because the LP and MIP objectives coincide to numerical precision in the evaluated instance, the reported schedule also verifies the integer cross-check. Figure 1 illustrates the resulting dispatch trajectory, and Table 1 summarizes the deterministic results.

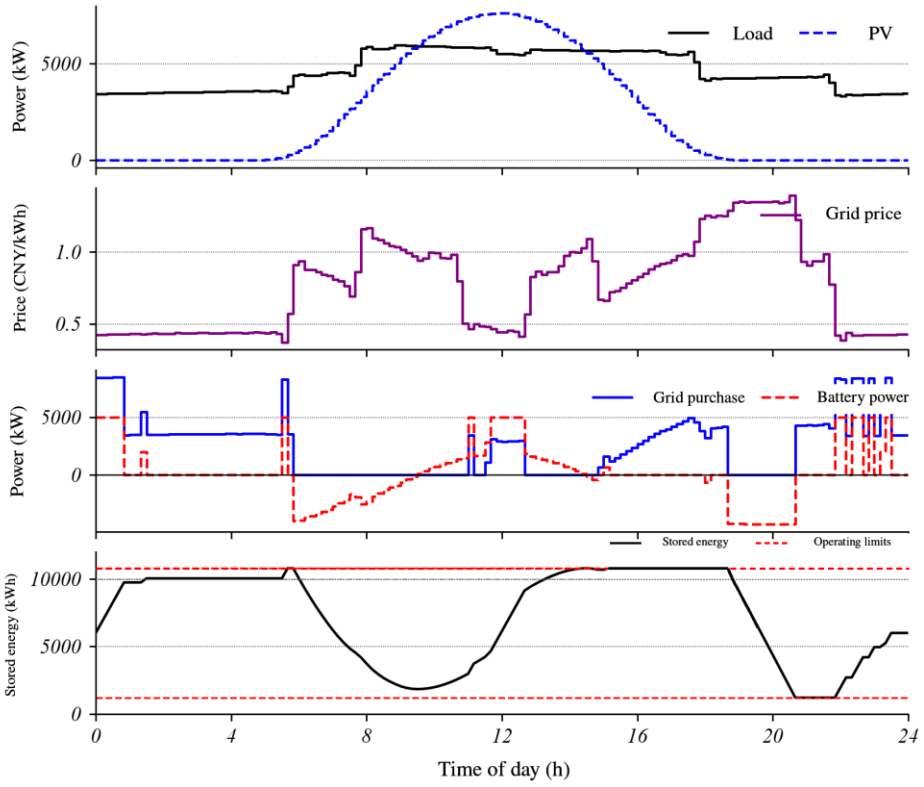


Figure 1. Full-day purchase, storage and unused-photovoltaic trajectory under the deterministic baseline.

Table 1. Deterministic full-information results.

Metric	With storage	No-storage baseline	Change
Purchase cost / CNY	35126.95	48052.05	-12925.10
Purchase energy / kWh	59482.70	Not reported as a separate baseline	Reference
Cost reduction	26.90%	0	26.90 percentage points
Maximum balance residual	2.27×10^-13 kWh	Verification	Numerical zero

The storage device is operated between 1,200 and 10,800 kWh, with 5,000 kW maximum charge and discharge power. The result illustrates the value of temporal energy transfer: the schedule charges during low-price or photovoltaic-surplus intervals and discharges when the net load and price make ordinary purchase expensive. The conclusion is conditional

on the evaluated price, load and PV profiles; it is not a claim that storage always lowers cost under different market rules.

4. Historical-Error Day-Ahead Scenario Optimization

4.1. Forecast and Residual Construction

The day-ahead layer uses the nearest W=2 same-weekday load curves and the nearest H=7 daily PV averages. Historical residual pairs are taken from R=14 completed days. The residuals are added to the current forecast before the scenario balance is formed, preserving the within-day co-movement between load and PV error.

$$\hat{L}_{d,t} = \frac{1}{W_d}\sum_{j=1}^{W_d} L_{d-7j,t} \quad (7)$$

$$\varepsilon^{L}_{\mathrm{h,t}} = L_{\mathrm{h,t}} - \hat{\mathrm{H}}_{\mathrm{h,t}}, \varepsilon^{\mathrm{PV}}_{\mathrm{h,t}} = P^{\mathrm{PV}}_{\mathrm{h,t}} - \hat{\mathrm{H}}^{\mathrm{PV}}_{\mathrm{h,t}} \quad (8)$$

The scenario residual is clipped into the nonnegative net-load or emergency-purchase representation, and each historical residual pair remains matched to its original day. The evaluation period contains 334 days from February 1 to December 31. It includes 48,096 ten-minute intervals, so the model evaluates a long sequence of daily schedules rather than a single representative day. Figure 2 shows the median load and PV profiles used to construct these historical-error scenarios.

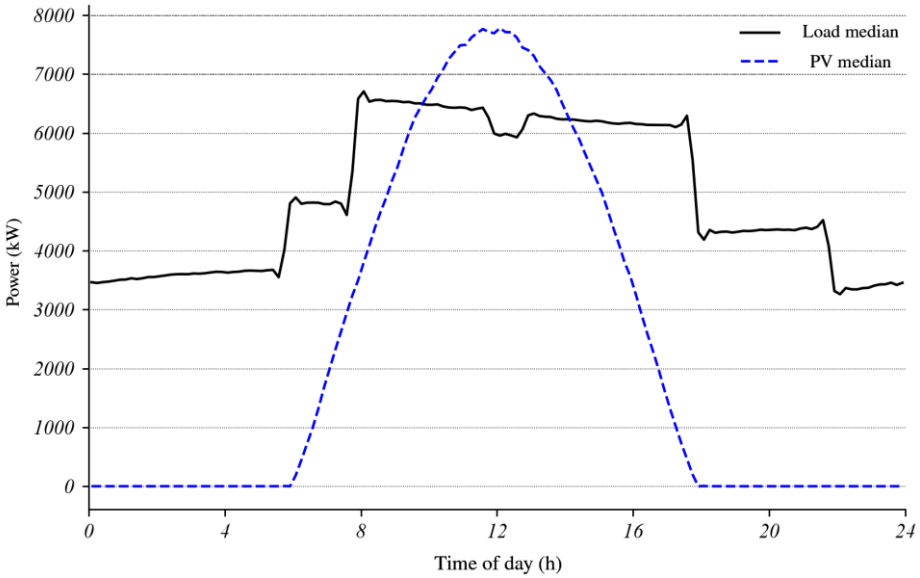


Figure 2. Median daily load and PV profile used to construct the historical-error scenarios.

4.2. Scenario LP and Results

The scenario linear program shares the ordinary purchase, charge, discharge and storage decisions across scenarios, while emergency purchase h_t^(s) absorbs the forecast residual. The objective adds a scenario-weighted penalty to emergency energy. Under the selected historical windows, the total evaluation cost is 14,731,085.32 CNY and emergency purchase is 300,628.68 kWh. A 48-hour cross-day comparison costs 14,797,771.46 CNY and does not improve the evaluation objective, so the reported method retains the day-ahead scenario plan. Table 2 summarizes the resulting day-ahead scenario performance.

Table 2. Historical-error day-ahead scenario results.

Evaluation item	Result
Forecast windows	W=2 same-weekday load; H=7 recent PV days
Residual history	R=14 completed days
Evaluation period	334 days; 48,096 ten-minute intervals
Total cost	14,731,085.32 CNY
Emergency purchase	300,628.68 kWh
48-hour comparison cost	14,797,771.46 CNY

5. Intraday Rolling Correction

The rolling layer separates a plan from its execution. A plan is generated at 00:00, while new PV forecasts arrive at 06:00, 12:00 and 18:00. At each update, executed intervals, measured storage state and already observed demand are fixed. Only the remaining ordinary-purchase decisions and the storage trajectory after the current state are re-optimized. This is a receding-horizon finite-state dynamic-programming layer built on the same physical ledger, not a new physical model.

$$q_{\mathrm{d,t}} = q^{0}_{\mathrm{d,t}} + u_{\mathrm{d,t}} - v_{\mathrm{d,t}}, u_{\mathrm{d,t}} = \max\left(q_{\mathrm{d,t}} - q^{0}_{\mathrm{d,t}}, 0\right), v_{\mathrm{d,t}} = \max\left(q^{0}_{\mathrm{d,t}} - q_{\mathrm{d,t}}, 0\right) \quad (9)$$

The day-ahead plan uses a normal purchase cost, while a rolling correction charges 1.5 times the tariff for upward adjustment, 0.5 times the tariff for downward adjustment and five times the tariff for emergency purchase. A small positive coefficient only breaks ties between physically equivalent actions. The dynamic state layer uses a discrete storage grid S={1200,1320,...,10800} and a backward Bellman recursion to select feasible storage actions. The terminal condition is V_T(E)=0 at E=6000 kWh and +∞ otherwise.

$$V_t(E) = \min_{E' \in S, |\psi(E'-E)| \le M}\{f_t + V_{t+1}(E')\} \quad (10)$$

The complete four-update strategy costs 13,905,968.07 CNY, compared with 16,143,244.46 CNY for the 00:00-only plan. It saves 2,237,276.39 CNY, or 13.8589%, while emergency purchase decreases from 636,769.98 to 117,452.29 kWh, a reduction of 81.55%. The result demonstrates the value of state feedback: it changes the remaining storage trajectory before the next forecast error is fully converted into emergency purchase. Figure 3 presents the day-ahead plans and storage trajectories at the four update

times, and Table 3 summarizes the rolling-correction results.

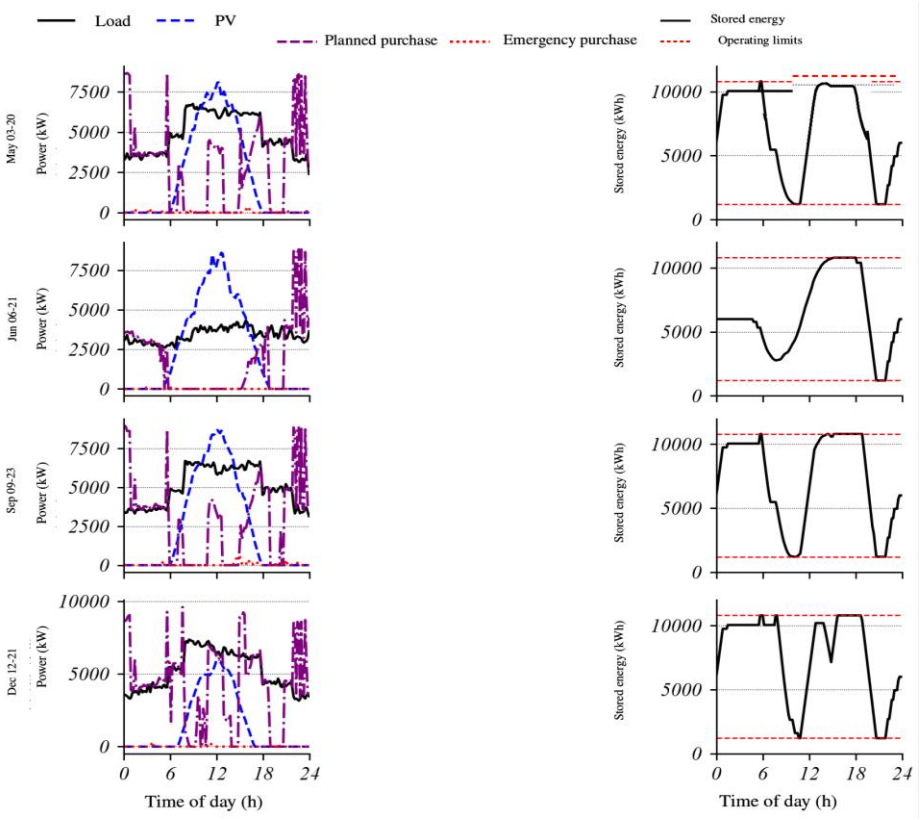


Figure 3. Day-ahead plans and storage trajectories at four forecast-update times.

Table 3. Rolling correction results.

Strategy	Total cost / CNY	Emergency purchase / kWh	Interpretation
00:00-only plan	16,143,244.46	636,769.98	No intraday correction
06:00+12:00+18:00 rolling	13,905,968.07	117,452.29	Feedback-corrected plan
Saving or reduction	13.8589%	81.55%	Relative to baseline

6. Time-Varying Price Scenarios

6.1. Price Forecast and Scenario Construction

The price layer uses the average of the same time interval over the previous 14 days. The 365-day price series has a minimum of 0.0076, a mean of 0.7575 and a maximum of 1.7936 CNY/kWh. Historical price residuals are paired with load residuals by day so that the scenario retains the dependence between net load and price. A positive floor of 0.001 CNY/kWh prevents an artificial negative price.

$$\hat{p}_{d,t} = \frac{1}{H_d}\sum_{j=1}^{H_d} p_{d-j,t} \tag{11}$$

$$p_{d,t}^{(s)} = \max\{0.001, \hat{p}_{d,t} + \varepsilon_{s,t}^{p}\} \tag{12}$$

6.2. Day-ahead and Intraday Price Optimization

The day-ahead price strategy fixes the shared purchase and storage variables at 00:00, while the intraday strategy updates photovoltaic information at 06:00, 12:00 and 18:00. Both strategies use the same power balance, storage bounds and charge-discharge exclusivity. The day-ahead objective combines ordinary purchase with scenario-weighted emergency cost; intraday updates minimize the remaining-horizon adjustment, emergency-purchase and tie-breaking terms. The remaining-horizon update uses the same 1.5/0.5 adjustment coefficients and fivefold scenario-weighted emergency term.

$$\min \sum_{t=0}^{T-1}\bar{p}_t q_t + \frac{5}{S}\sum_{s=1}^{S}\sum_{t=0}^{T-1} p_t^{(s)} h_t^{(s)} \tag{13}$$

The day-ahead and intraday strategies cost 17,277,452.76 and 17,288,271.78 CNY, respectively. The intraday strategy reduces emergency purchase from 285,846.08 to 175,265.45 kWh, or 38.6854%, but total cost increases by 10,819.02 CNY, or 0.0626%. The difference is a useful warning: lower emergency purchase does not guarantee lower total cost when adjustment fees and price timing are included. Figure 4 compares annual cost and emergency purchase; Table 4 gives the corresponding values, while Figure 5 illustrates a representative-day profile.

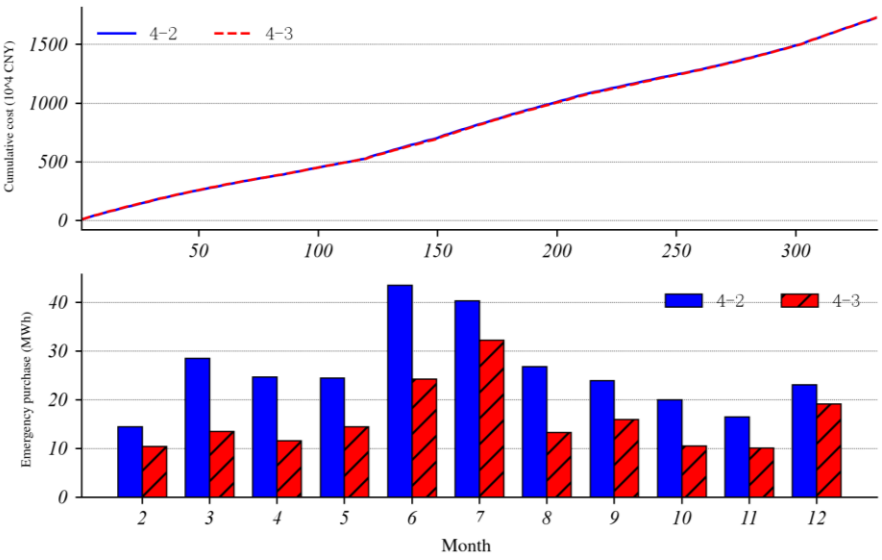


Figure 4. Annual cost and emergency-purchase comparison under the two time-varying-price strategies.

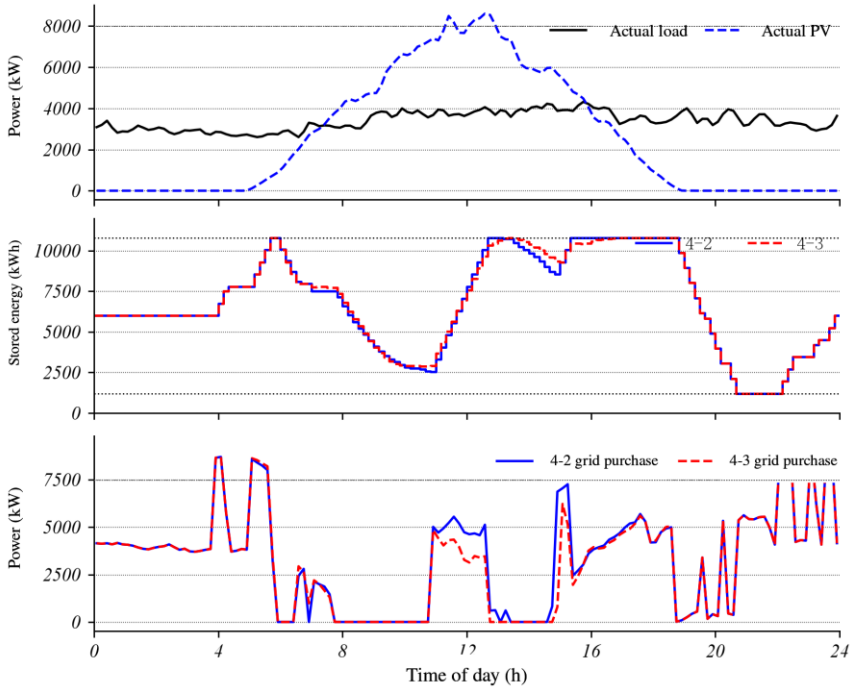


Figure 5. Representative day showing load, PV, storage and ordinary purchase under the price strategies.

Table 4. Price-scenario comparison.

Strategy	Total cost / CNY	Emergency purchase / kWh	Relative result
Day-ahead price strategy	17,277,452.76	285,846.08	Lower total cost
Intraday price strategy	17,288,271.78	175,265.45	38.6854% less emergency energy
Intraday minus day-ahead	+10,819.02	-110,580.63	Cost rises 0.0626%

7. Integrated Evaluation and Conclusions

The four settings share a common physical and accounting core but answer different information questions. The deterministic schedule measures the pure value of storage when the day is known. The historical-error scenario measures the cost of preparing for forecast residuals. Rolling correction measures the value of state feedback after execution. The price scenario measures the economic value of updated tariff information when adjustment and emergency costs are both present. Table 5 consolidates the results across the four information settings.

Table 5. Integrated results under the four information settings.

Information setting	Main result	Engineering interpretation
Full-information intraday	35,126.95 CNY; 26.90% below no-storage baseline	Storage transfers energy across price and PV periods
Historical-error day-ahead	14,731,085.32 CNY; 300,628.68 kWh emergency purchase	Forecast residuals require scenario protection
06/12/18 rolling correction	13,905,968.07 CNY; 81.55% emergency reduction	State feedback absorbs realized deviations
Time-varying price intraday	17,288,271.78 CNY; 38.6854% emergency reduction	Information reduces emergency energy but may add adjustment cost

The modeling contribution is the common accounting boundary. Every comparison retains the same ten-minute conversion, storage efficiency, operating range, charge-discharge exclusivity, nonnegativity and terminal-state convention. Only the information available at the decision time changes. This prevents a lower cost from being incorrectly attributed to a new physical device when it actually comes from forecast access or a different settlement rule.

Numerical verification also supports the reported results. Recomputed energy balances, storage recursion, feasible-state transitions and cost components agree to numerical precision. The conclusions are therefore limited to the terminal-storage, no-sale and empirical-scenario assumptions used in this study. Battery degradation, network constraints, reserve markets and forecast distributions beyond the historical sample are not represented by the available data and should be added before deployment.

8. Conclusions

This study supports the computational feasibility of a unified physical and accounting framework for electricity-purchase and storage scheduling in a PV-storage microgrid. Using one ten-minute ledger, it applies linear programming, finite-state dynamic programming and scenario optimization to four information settings while retaining a common power balance, storage range, efficiency and terminal-state convention. The 334-day evaluation, together with numerical checks of energy balance, storage recursion, feasible-state transitions and cost components, supports consistent comparison at the tested resolution.

The full-information schedule costs 35,126.95 CNY, 26.90% below the no-storage baseline; historical-error scenarios yield 14,731,085.32 CNY over 334 days. Rolling updates at 06:00, 12:00 and 18:00 reduce cost by 13.8589% and emergency purchases by 81.55%. Under time-varying prices, intraday updating cuts emergency purchases by 38.6854%, while total cost increases by 0.0626%. These findings show that storage, forecast feedback and tariff information should be assessed together when designing practical purchase policies.

The present findings are limited by the terminal-SOC, no-export, fixed-efficiency and empirical-scenario assumptions, and by the omission of battery degradation, network constraints, reserve markets and out-of-sample forecast distributions. Future work should incorporate these operational factors and test the framework across additional microgrids, seasons and tariff structures. Pilot deployments can then assess update latency, operational feasibility and realized cost savings under real-time data.

References

[1] Farzin, H., Fotuhi-Firuzabad, M., & Moeini-Aghtaie, M. (2017). A stochastic multi-objective framework for optimal scheduling of energy storage systems in microgrids. IEEE Transactions on Smart Grid, 8(1), 117–127.

[2] Schwenzer, M., Ay, M., Bergs, T., & Abel, D. (2021). Review on model predictive control: an engineering perspective. International Journal of Advanced Manufacturing Technology, 117, 1327–1349.

[3] Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, M., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., … SciPy 1.0 Contributors. (2020). SciPy 1.0: fundamental algorithms for scientific computing in Python. Nature Methods, 17, 261–272.

[4] Tsianikas, S., Yousefi, N., Zhou, J., Rodgers, M., & Coit, D. W. (2021). A storage expansion planning framework using reinforcement learning and simulation-based optimization. Applied Energy, 290, 116778.

[5] Zhou, K. S., Zhou, K. L., & Yang, S. L. (2022). Reinforcement learning-based scheduling strategy for energy storage in microgrid. Journal of Energy Storage, 51, 104379.

[6] Guo, C. Y., Wang, X., Zheng, Y. H., & Zhang, F. (2022). Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning. Energy, 238, 121873.

[7] Tobajas, J., Garcia-Torres, F., Roncero-Sanchez, P., & Torres-Moreno, J. L. (2022). Resilience-oriented schedule of microgrids with hybrid energy storage system using model predictive control. Applied Energy, 306, 118092.

[8] Hu, C. C., Cai, Z. X., Zhang, Y. X., Lin, Z. Z., & Zhang, H. G. (2022). A soft actor-critic deep reinforcement learning method for multi-timescale coordinated operation of microgrids. Protection and Control of Modern Power Systems, 7, 29.

[9] Zhu, Z. S., Weng, Z. M., & Zheng, H. L. (2022). Optimal operation of a microgrid with hydrogen storage based on deep reinforcement learning. Electronics, 11(2), 196.

[10] Jiao, F., Zou, Y., & Zhang, Y. (2022). Online optimal dispatch based on combined robust and stochastic model predictive control for a microgrid including EV charging station. Energy, 247, 123220.

[11] Harrold, D. J. B., Cao, J., & Fan, Z. (2022). Renewable energy integration and microgrid energy trading using multi-agent deep reinforcement learning. Applied Energy, 318, 119151.

[12] Li, Q., Zou, X. L., Pu, Y. C., & Liu, Y. (2023). Optimal schedule of combined heat-power microgrid based on hydrogen energy storage. Journal of Southwest Jiaotong University, 58(1), 9–21. (in Chinese)

[13] Zheng, Y., Zhu, S. F., Yang, D. X., & Li, J. (2025). A multi-time scale optimal dispatch strategy for green ammonia production using wind-solar hydrogen under renewable energy fluctuations. Energies, 18(24), 6518.