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Optimal Day-Ahead Dispatch of a Grid-Connected Microgrid with Energy Storage under Time-of-Use Pricing and Load Uncertainty

Junjie Ma *

Department of Mechanical, Electrical and Materials Engineering XuHai College of China University of Mining and Technology, Xuzhou, 221008, China

* **Corresponding author**: (Email: 18261541256@163.com)

Abstract: Microgrid energy management must balance a time-of-use electricity purchase plan against battery storage dispatch so that the total purchase cost is minimised while all physical constraints on state of charge and charge/discharge power are satisfied. Existing studies rely onnonlinear economic model predictive control orrolling-horizon optimisation, which restore feasibility online but do not guarantee a global optimum, and onprice-arbitrage battery scheduling that treats the tariff in isolation. Model constructs a two-stage framework that first partitions the tariff into three tiers by partitioning-around-medoids clustering with a silhouette coefficient of 0.772 and then solves a deterministic day-ahead dispatch with linear programming and an equivalent big-M mixed-integer program, which yields a globally optimal schedule with zero simultaneous charge/discharge slots. Day-ahead uncertainty is absorbed by a quantile safety margin plus penalised emergency purchase. The deterministic scheme lowers the daily purchase cost from 48,052.05 to 35,126.95 yuan, a 26.90% saving, and the annual two-stage cost is 14,066,913.87 yuan. Compared with online controllers, the model offers a global optimum guarantee, an explicit three-tier price interpretation, and atractable safety margin.

Keywords: Microgrid Dispatch, Energy Storage, Time-of-use Pricing, Mixed-integer Linear programming.

1. Introduction

Microgrids integrate distributed generation, energy storage, and flexible loads into a locally controllable power system, and their economic operation has become a central research topic as renewable penetration continues to grow. A grid-connected microgrid can purchase electricity from the upstream network under a time-of-use tariff and arbitrage the price difference through battery storage; the core task is therefore to decide, for every dispatch interval, how much power to buy and how much to charge or discharge so that the total purchase cost is minimised while all physical constraints remain satisfied.

Existing work approaches this task from several directions. Nonlinear economic model predictive control formulates the dispatch as an online optimisation and handles time-varying prices and forecasts, but the resulting problem is non-convex and only certifies a local, receding-horizon optimum [1]. Distributed economic model predictive control decomposes the microgrid into subsystems and reduces the per-node computational burden, yet it inherits the same lack of a global-optimality certificate [2]. Studies on residential battery scheduling quantify the arbitrage revenue of price-driven storage and show that a storage device is profitable only when the peak-to-valley spread exceeds the round-trip loss [3]; intraday-market battery optimisation further demonstrates that price uncertainty materially changes the optimal bidding and charging policy [4]. Shared-storage scheduling for rural microgrids confirms that coordinated storage dispatch lowers operating cost, but it relies on scenario-based formulations [5]. On the load side, clustering of electricity load profiles reveals strong behavioural regularity that can be exploited for segmentation and forecasting [6]. Rolling-horizon optimisation under uncertainty [7, 8] supplies a practical online re-dispatch framework, and day-ahead probabilistic photovoltaic forecasting [9, 10] provides the uncertainty description required by stochastic dispatch. Model-data hybrid methods further combine optimisation with learning for multi-microgrid economic dispatch [11].

Despite this progress, three gaps remain. First, most online controllers trade global optimality for feasibility, so the achieved cost is not provably the minimum for the day. Second, the time-of-use structure is rarely exploited in an interpretable way; clustering the tariff into a small number of tiers makes the arbitrage logic explicit and verifiable. Third, day-ahead uncertainty is usually handled by scenario trees or robust sets that are difficult to calibrate in practice. This paper addresses these gaps with a two-stage framework. In the first stage the paper cluster the tariff into three tiers by partitioning around medoids and solve a deterministic day-ahead dispatch with linear programming, whose physical feasibility is enforced by an equivalent big-M mixed-integer linear program with a binary charge/discharge indicator. In the second stage it absorbs day-ahead forecast error by a quantile safety margin and a penalised emergency purchase, yielding a two-stage plan-then-settle schedule. Compared with the cited controllers, our model guarantees a global optimum for the deterministic day, exposes an explicit three-tier price interpretation of the arbitrage, and replaces intractable scenario trees with a single calibrated safety margin. The remainder of the paper is organised as follows. Section 2 establishes the physical model and the two-stage optimisation; Section 3 reports the deterministic and uncertainty-aware results; Section 4 concludes.

2. Model Establishment

2.1. Problem Description and Physical Model

The microgrid under study is a single-bus, grid-connected system that contains a photovoltaic generator, a battery energy storage unit, and an aggregated load. It is not islanded: the bus is connected to the upstream distribution network and may buy electricity at any time, so supply adequacy is guaranteed by the grid and the optimisation goal is purely economic. The day is discretised into 144 slots of ten minutes each, and the storage device is described by a rated capacity, a maximum charge/discharge power, and a one-way efficiency that applies symmetrically to charging and discharging. The relevant physical constants are collected in Table 1.

Table 1. Physical Parameters of the Microgrid System

Symbol	Value	Meaning
T	144	dispatch slots per day, ten-minute granularity
Δt	1/6 h	duration of one slot
η	0.9	one-way charge/discharge efficiency
E_{max}	12,000 kWh	rated storage capacity
P_{max}	5,000 kW	Maximum charge/discharge power
M	833.33 kWh	big-M bound, equal to P_{max}·Δt
E_{min} E_{max}	1,200 / 10,800 kWh	state-of-charge operating window
$E_0 = E_t$	6,000 kWh	initial and final state of charge

Let E_t denote the stored energy at the end of slot t, c_t the charging energy, and d_t the discharging energy within slot t. The state-of-charge recursion that couples consecutive slots is

$$E_t = E_{t-1} + \eta c_t - \frac{d_t}{\eta}, t = 1, \dots, T \quad (1)$$

The round-trip efficiency η^2 = 0.81 is the reason that every charge/discharge cycle must earn a price spread larger than the loss before it becomes profitable, which is exactly the arbitrage condition verified in the results. Let g_t be the energy purchased from the grid and l_t the net load, defined as the load minus the photovoltaic output. The bus energy balance is

$$g_t + d_t = l_t + c_t, t = 1, \dots, T \quad (2)$$

Because charging and discharging a battery at the same instant is physically meaningless and cannot be distinguished by a purely linear model, the deterministic dispatch is also formulated as a mixed-integer program. A binary indicator u_t gates the two directions through a big-M constraint,

$$0 \le c_t \le M u_t, 0 \le d_t \le M(1 - u_t), u_t \in \{0,1\} \quad (3)$$

And the storage is confined to its operating window with a periodic boundary condition,

$$E_{min} \le E_t \le E_{max}, E_0 = E_T = 60\ kWh \quad (4)$$

2.2. Time-of-Use Price Clustering by Partitioning Around Medoids

The tariff is a stepwise price series that repeats every day, but treating all 144 price slots as free variables obscures the arbitrage structure. The paper therefore compress the tariff into a small number of tiers before dispatch. Partitioning around medoids is chosen over k-means for three reasons: it works with Manhattan distance, which matches the absolute price differences that drive arbitrage; its cluster centres are real tariff samples rather than arithmetic means, so every tier remains an actually occurring price; and it is robust to the skewed price distribution. For a chosen number of medoids K, the objective is to minimise the total distance from every sample to its nearest medoid,

$$J = \sum_{i=1}^{n} min\ m_k \in M\ |p_i - m_k| \quad (5)$$

The number of tiers is selected jointly by the silhouette coefficient and the within-cluster sum of squared errors. The silhouette of sample i,

$$s(i) = \frac{b(i) - a(i)}{max\{a(i), b(i)\}} \quad (6)$$

Contrasts the mean intra-cluster distance a(i) with the mean nearest-other-cluster distance b(i). Scanning K from 2 to 5 shows that the silhouette reaches its maximum 0.772 at K = 3 and falls to 0.7424 at K = 4, while the squared-error reduction slows from 44.1% between K = 2 and K = 3 to 32.4% between K = 3 and K = 4. Both criteria therefore point to three tiers, which are naturally interpreted as valley, flat, and peak periods.

2.3. Deterministic Day-Ahead Dispatch by Linear and Mixed-Integer Programming

With the three tiers fixed, the deterministic problem is a single-day cost minimisation. The linear program chooses the purchase, charge, and discharge schedule that minimises the purchase cost subject to equations (1), (2), and (4):

$$min \sum_{t=1}^{T} p_t\ g_t \quad (7)$$

Because the objective is linear and all constraints are linear equalities or inequalities, the linear program is convex and any solver certificate is a global optimum. The mixed-integer program uses the same objective and constraints but adds the binary gate of equation (3), which forbids simultaneous charge and discharge. The big-M constant M = P_{max} ·Δt = 833.33 kWh is exactly the largest energy that can be charged or discharged in one slot, so the gate is tight rather than conservative. Solving both formulations verifies that the relaxation does not hide any infeasible simultaneous action and that the two optimal costs coincide.

2.4. Day-Ahead Uncertainty and the Two-Stage Settlement

The deterministic model assumes the next-day net load is known, which does not hold in practice. The work therefore predicts the load with a same-weekday nearest-neighbor mean: the forecast for slot t of day d is the average of the last k = 4 same weekdays,

$$L\hat{}_t^{(d)} = \frac{1}{k}\sum_{j=1}^{k} L_t^{(d-7j)}, k = 4 \quad (8)$$

Photovoltaic output has no weekly rhythm and is instead dominated by recent climate conditions, so it is forecast by the mean of the most recent days. The net load is then

$$n_t = L_t \Delta t - P_t^{PV} \Delta t \quad (9)$$

A point forecast cannot remove the risk that the realized net load exceeds the plan, which would force an emergency purchase at a fivefold price. The study therefore raise the target net load by a safety margin that is the ρ-quantile of the trailing thirty-day forecast residual,

$$n\sim_t^{(d)} = n\hat{}_t^{(d)} + Q_\rho(\varepsilon_t^{(d-30:d-1)}) \quad (10)$$

Where the residual ε is the historical difference between the realized and the forecast net load. The day-ahead plan is obtained by solving the same linear program with the inflated net load, and the real-time stage settles any remaining shortfall as emergency energy at five times the tariff. The two-stage cost is therefore

$$C = \sum_{t=1}^{T} p_t \, g_t^{plan} + 5 \sum_{t=1}^{T} p_t \, e_t \quad (11)$$

A larger margin makes the plan more conservative and reduces emergency energy, but it also increases ordinary purchase, so the margin is selected by minimising the annual total cost on a grid of candidate values.

2.5. Advantages of the Proposed Model

The two-stage construction offers three concrete advantages over the cited approaches. First, the deterministic stage is a convex linear program whose solution is a provable global optimum, in contrast to the local optima of nonlinear and receding-horizon controllers. Second, clustering the tariff before dispatch turns the arbitrage decision into an interpretable valley-charge and peak-discharge rule, which is absent from black-box controllers and from price-arbitrage models that operate on the raw series. Third, the safety margin replaces a scenario tree or a robust uncertainty set with a single quantile that is estimated directly from the trailing residual distribution, so it is both computationally cheap and easy to calibrate. These properties are quantified in the results section, where the same physical kernel is solved deterministically and then under uncertainty.

3. Results

3.1. Deterministic Day-Ahead Dispatch

The tariff is first clustered into three tiers, and the resulting tier structure is reported in Table 2. The peak tier contains only 20 of the 144 slots but its mean price 1.2976 yuan/kWh is nearly three times the valley mean, which already indicates a substantial arbitrage margin.

Table 2. PAM clustering results for time-of-use electricity prices

Tier	Mean price (yuan/kWh)	Slots
Valley	0.4471	62
Flat	0.9139	62
Peak	1.2976	20

The linear program and the big-M mixed-integer program are then solved on a representative day. Their optimal costs are identical to four decimal places, and neither formulation produces a single simultaneous charge/discharge slot, which confirms that the relaxation is tight. Compared with the no-storage baseline, storage lowers the daily purchase cost as shown in Table 3.

Table 3. Representative-Day Scheduling Results and No-Storage Baseline Comparison

Metric	No-storage baseline	Linear program	big-M mixed-integer program
Purchase cost (yuan)	48,052.05	35,126.95	35,126.95
Simultaneous charge/discharge slots	—	0	0

The 12,925.10 yuan saving corresponds to a 26.90% reduction. The dispatch schedule itself uses 45 charging slots and 37 discharging slots; the average price at which energy is charged is 0.4930 yuan/kWh, while the average price displaced by discharge is 1.1376 yuan/kWh, giving a spread of 0.6446 yuan/kWh that comfortably exceeds the round-trip loss. Charging is concentrated in the valley tier and discharging in the peak tier: 87.7% of charging occurs in valley slots and 56.2% of discharging in peak slots, so the purchase profile shifts strongly toward cheap periods, with 71.6% of purchases in the valley, 21.8% in the flat, and only 6.6% in the peak tier. Over the day the microgrid buys 59,482.70 kWh, charges 20,740.67 kWh, and discharges 16,799.94 kWh; the 3,940.73 kWh difference is exactly the round-trip loss implied by the 0.9 one-way efficiency, and the state of charge returns from 6,000 kWh to 6,000 kWh.

3.2. Day-Ahead Uncertainty and Safety Margin

The two-stage model is evaluated over the full year of 334 days. The load forecast uses k = 4 same weekdays and the photovoltaic forecast uses the climate-state mean, and the safety margin is selected on a grid of candidate values. The annual result at the selected margin is summarized in Table 4.

Table 4. Annual Results of the Two-Stage Model Under the Selected Safety Margin

Item	Result
Optimal safety margin ρ*	0.9
Annual total cost (yuan)	14,066,913.87
Planned purchase cost (yuan)	13,760,797.75
Emergency purchase cost (yuan)	306,116.12
Annual emergency energy (kWh)	53,295.78

The benefit of the margin is measured against a plan that injects no margin at all. Without the margin the annual cost is 14,343,900 yuan and the emergency energy reaches 236.40 MWh; the chosen margin adds about 780,000 yuan of ordinary planned purchase, which is far outweighed by a 77% reduction in emergency energy, producing a net annual saving of about 277,000 yuan. Sweeping the margin from 0.3 to 0.95 shows that emergency energy falls monotonically from 1,285.9 MWh to 26.0 MWh, while the total cost follows a U shape that bottoms near ρ = 0.8 at 13,930,214 yuan. The ρ = 0.8 and ρ = 0.9 costs differ by only about 1.0%, but their emergency energies differ by 57.2%, so ρ* = 0.9 is selected as the economic-reliability trade-off.

The emergency energy is highly concentrated. Across the

year only 80 of 334 days incur any emergency purchase, and the remaining 254 days, 76.0% of the total, are exactly zero. The five largest emergency days, at 6,907.3, 4,574.1, 3,477.6, 3,248.4, and 2,524.0 kWh, together account for 38.9% of the annual emergency energy, and the single largest day contributes 13.0%. This long-tail concentration implies that the shortage arises from a few extreme forecast-error days rather than from a general scarcity of photovoltaic output. The net load across the year spans from −352.9 to 826.1 kWh per slot, and the daily planned cost ranges from 13,233 to 67,445 yuan with a mean of 41,200 yuan, a spread equal to 83% of the mean that reflects the strong seasonal variation and justifies solving every day rather than relying on a single typical day. On the four designated dates, emergency purchase is zero on 2025-03-20, 2025-06-21, and 2025-12-21, while 2025-09-23 requires a single slot of 6.375 kWh at a cost of 43.00 yuan.

4. Conclusions

The method selection in this paper precisely matches the problem structure: the four sub-problems respectively adopt linear programming and mixed-integer programming, two-stage plan simulation, rolling horizon optimization, and a prediction-plus-framework approach, targeting different sources of uncertainty without omission. All sub-problems share a unified energy balance and SOC recursion kernel, with modular progression and verifiable results. The framework strictly distinguishes "prediction for decision-making" from "measured data for settlement," avoiding information leakage. Key designs closely follow the problem requirements, and exact algorithms with fixed random seeds ensure reproducibility. The layered framework has strong transferability and can be extended to scenarios such as park demand response, building energy storage, orderly charging of EV charging stations, and virtual power plants. The nearest-neighbor prediction in Problem 2 is relatively simple, still leaving a gap of about 117,000 yuan from perfect foresight; future work could introduce time-series deep learning or probabilistic forecasting and further study joint prediction-decision optimization. The safety margin and adjustment threshold are currently tuned offline and could be developed into adaptive online updating combined with rolling forecasts. The constant energy storage efficiency does not account for nonlinear characteristics varying with SOC and charge-discharge rate, which could be refined in modeling. Multi-agent aggregation, robust configuration, online optimization, and three-stage market mechanisms in the extension scenarios also merit further investigation.

The forecasting method in Problem 2 is relatively simple, still leaving a gap of about 117,000 yuan from perfect foresight; the safety margin and adjustment threshold rely on offline tuning and have not yet achieved online adaptivity; the energy storage efficiency is set as a constant, without considering nonlinear characteristics varying with SOC and charge-discharge rate; and the multi-agent aggregation and three-stage market mechanisms in the extension scenarios have not yet been explored in depth.

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