A Study on the Dynamic Pricing with Strategic Energy Storage in P2P Microgrids Systems

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P2P 마이크로그리드 시스템에서 전략적 에너지 저장을 통한 동적 가격 책정에 관한 연구

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Abstract

This study introduces a dynamic pricing strategy tailored for peer-to-peer (P2P) energy trading within residential microgrids, aiming to enhance the coordination between trading behavior and distributed energy storage. A multi-agent system is developed in which prosumers with battery storage can strategically time their market participation based on forecasted renewable generation, expected prices, and local demands. The proposed two-stage pricing mechanism combines forecast-based price formation with real-time adjustments, enabling prosumers to optimize their energy storage and trading strategies. Simulation results demonstrate that the integration of strategic battery usage leads to improved market efficiency, reduced price volatility, and enhanced energy self-consumption within the microgrid community.

I. Introduction

Peer-to-peer (P2P) energy trading allows households that generate their own electricity to exchange surplus energy directly within their local community, reducing reliance on centralized utilities. Although many recent studies have examined the design of P2P trading systems [1-4], the interaction between market participation and energy storage strategies has received relatively limited attention. This paper seeks to address that gap by introducing a dynamic pricing model that explicitly incorporates the role of distributed storage in residential microgrids.

By enabling users to shift energy use across time, storage systems introduce new degrees of flexibility into trading decisions. Prosumers can choose to hold back from selling during periods of low market prices or delay purchasing when prices peak, creating more dynamic and strategic market behavior than in storage-free settings. The approach explores how pricing schemes can be structured to coordinate these decisions effectively, maintaining both economic efficiency and market stability.

Ⅱ. Method

The proposed methodology involves a residential microgrid composed of N prosumers, each equipped with the following components:

- Renewable energy generation (primarily solar photovoltaic systems),
- Battery storage with a maximum capacity B_i and charge/discharge efficiency η_i,
- Time-varying load profiles $L_i(t)$.

At each time interval t, prosumer i makes decisions regarding:

- The amount of energy exchanged with peers in the network, represented by $E_i^{trade}(t)$,
- The amount of energy charged to or discharged from battery, denoted as $E_i^{battery}(t)$.

The net energy balance constraint for each prosumer is:

$$L_i(t) = G_i(t) + E_i^{battery}(t) + E_i^{trade}(t),$$

where $G_i(t)$ indicates the energy generated from renewable sources by prosumer i at time t.

To facilitate efficient and adaptive trading behavior, a two-stage pricing mechanism is introduced that reflects both forecast expectations and real-time market dynamics:

- Forecast-Based Price Formation when each prosumer submits forecasted generation, load, and expected storage availability. Forecast-based price formation relies on accurate predictions of generation and demand, which can be improved using advanced data-driven methods [5]. The system forms initial price projections $P_{forecast}(t)$ for each interval in the upcoming trading window: $P_{forecast}(t)$=P_{base} + $\alpha_{forecast} \times (D_{total}(t) - G_{total}(t))$.
- As actual generation data becomes available, prices are updated using:

$$P(t) = P_{forecast}(t) + \alpha \times (S_{actual}(t) - S_{forecast}(t)),$$

where $S(t)$ denotes the supply-demand balance, and α is a sensitivity parameter controlling the magnitude of real-time correction.

Each prosumer independently optimizes its storage and trading strategy over the time horizon by solving the following cost-minimization problem:

$$\min_{E_i^{trade}, E_i^{battery}} \sum_t P(t) \cdot E_i^{trade}(t) + C_i\left(E_i^{battery}(t)\right).$$

This objective accounts for both trading costs and battery degradation, captured by the convex function $C_i(\cdot)$, as discussed in [6], [7]. The optimization is subject to technical constraints on battery capacity, charging/discharging rates, and the local energy balance equation.

Ⅲ. Result and Analysis

The simulation considers a microgrid with 3 prosumers, each equipped with different battery capacities (6-12 kWh) and efficiencies (92-96%). Solar generation profiles follow realistic bell curves with peak generation around noon, while load profiles exhibit typical residential patterns with morning and evening peaks.

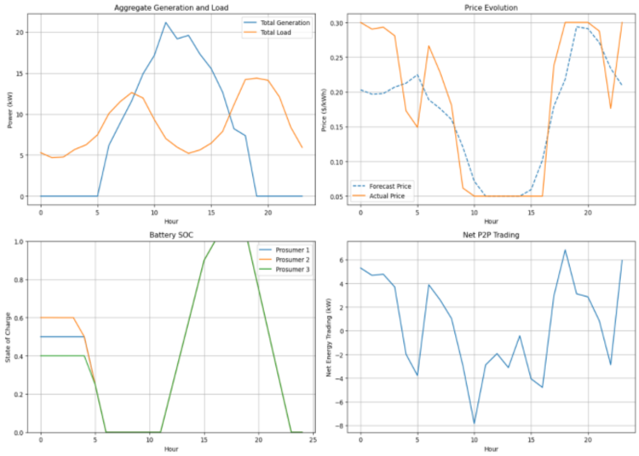

Fig 1. Prosumer 1 and Prosumer 2 before and after Peak Load Reduction

The simulation results over the 24-hour period are presented in Fig. 1, which shows the aggregate system behavior including generation and load profiles, price evolution, battery state of charge for three prosumers, and net P2P trading patterns.

The simulation results demonstrate significant differences between forecasted and actual prices, validating the effectiveness of the two-stage pricing mechanism. During solar peak hours (10-15h), actual prices dropped below forecasted prices due to strategic battery charging, while evening hours (18-22h) showed higher actual prices as prosumers discharged their batteries.

All prosumers exhibited optimal battery usage patterns, charging during low-price periods (when excess solar generation was available) and discharging during high-price periods.

Market Efficiency Metrics can be highlighted:

- Self-consumption rate: 44%,
- Grid independence: 63%,
- Average price: $0.186/kWh,
- Price volatility: $0.067/kWh.

Perfect energy balance is maintained throughout the simulation, with total generation of 179.68 kWh meeting total load of 207.96 kWh through strategic trading and grid imports.

The results reveal sophisticated trading strategies among prosumers:

- Arbitrage Operations: Prosumers consistently bought energy during low-price periods for storage and sold during peak-price periods,
- Strategic Battery Usage: As evident from the complete simulation results, optimal battery management allowed prosumers to effectively exploit price differences throughout the day,
- Coordinated Behavior: Despite individual optimization, collective behavior led to system-wide benefits with reduced overall energy costs.

IV. Conclusion

This study demonstrated that dynamic pricing with strategic energy storage effectively coordinates P2P energy trading in microgrids. The two-stage pricing mechanism enabled prosumers to optimize battery usage for temporal arbitrage, improving self-consumption and market efficiency. Simulation results showed optimal battery utilization and price responsiveness to real-time market conditions, providing a foundation for implementing practical P2P energy systems with integrated storage.

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