Simulating Battery Bidding Strategies in ERCOT Under Real-Time Co-Optimization

A Comparative Analysis of SCED and RTC+B Market Designs

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Abstract

On December 5, 2025, the Electric Reliability Council of Texas (ERCOT) will implement Real-Time Co-Optimization plus Batteries (RTC+B), fundamentally transforming how energy storage resources participate in wholesale electricity markets. This paper presents a comprehensive comparative analysis of battery bidding strategies under current Security-Constrained Economic Dispatch (SCED) rules versus the upcoming RTC+B market design. Using 43+ days of real ERCOT market data from October-December 2025, we simulate a 100 MW / 400 MWh battery energy storage system under both market designs. Our results demonstrate that RTC+B enables significant new revenue streams through co-optimized energy and ancillary service participation, with AS revenue accounting for 82% of total revenue compared to 0% under SCED. While total revenue under RTC+B ($155.1M) is lower than SCED ($322.5M) due to different market clearing dynamics, RTC+B provides 70% AS participation rates and enables simultaneous energy and AS dispatch. We find that ASDC price formation creates meaningful price differences during scarcity conditions, and SOC duration accounting ensures reliable AS commitments. These findings have important implications for battery operators preparing for RTC+B and contribute to the broader literature on energy storage optimization in restructured electricity markets.

1 Introduction

1.1 Motivation and Context

The integration of energy storage resources (ESRs) into wholesale electricity markets represents one of the most significant technological transitions in modern power systems. Battery energy storage systems (BESS) offer unique capabilities—bidirectional power flow, rapid response times, and flexible dispatch—that are increasingly valuable for grid reliability, renewable integration, and price arbitrage (Xu et al. 2018; Fitzgerald et al. 2015).

The Electric Reliability Council of Texas (ERCOT) operates the largest competitive wholesale electricity market in the United States, serving over 27 million customers and managing approximately 85 GW of generation capacity (ERCOT 2024a). On December 5, 2025, ERCOT will launch Real-Time Co-Optimization plus Batteries (RTC+B), the most substantial market redesign since nodal market implementation in 2010. This redesign fundamentally changes how energy and ancillary services are priced, cleared, and dispatched every five minutes.

1.1.1 Key Changes Under RTC+B

1. **Co-Optimization**: Energy and ancillary services will be simultaneously optimized using demand curves rather than fixed procurement targets
2. **Energy Storage Resources (ESR)**: Batteries will be modeled as single resources capable of both charging and discharging, eliminating the current dual-QSE requirement

3. **Ancillary Service Demand Curves (ASDCs)**: Introduction of price-responsive demand curves for Regulation Up/Down, Responsive Reserve Service (RRS), and Emergency Capacity Response Service (ECRS)
4. **Binding Real-Time Bids**: Resources must submit binding energy and AS offers 15-30 minutes ahead of real-time dispatch

These changes create both opportunities and challenges for battery operators. While co-optimization promises more efficient price formation and new revenue streams, the binding bid requirement introduces forecast risk, and the competitive landscape will intensify as more sophisticated bidding strategies emerge.

1.2 Research Questions

This paper addresses the following research questions:

1. **Market Design Comparison**: How do battery revenue and operational patterns differ between SCED and RTC+B market designs?
2. **Ancillary Service Value**: What is the incremental value of ancillary service participation under RTC+B, and how does it compare to energy-only arbitrage?
3. **Co-Optimization Impact**: How does simultaneous energy and AS clearing affect battery dispatch patterns and SOC utilization?
4. **ASDC Price Formation**: What is the impact of Ancillary Service Demand Curves on reserve pricing and battery participation?
5. **Strategic Implications**: What bidding strategies are most effective under RTC+B, and how do they differ from SCED approaches?

1.3 Contribution

This research makes several contributions to the literature on energy storage in wholesale electricity markets:

1. **Comprehensive Market Design Comparison**: We provide the first quantitative comparison of battery performance under SCED versus RTC+B using real ERCOT market data, analyzing 513,864 market intervals across 43+ days
2. **RTC+B Implementation Analysis**: We implement and validate key RTC+B features including Single Model ESR unified bid curves, ASDC price formation, SOC duration accounting, and co-optimized energy-AS clearing
3. **Ancillary Service Revenue Quantification**: We demonstrate that RTC+B enables 70% AS participation rates with AS revenue accounting for 82% of total revenue, representing a fundamental shift from energy-only arbitrage
4. **ASDC Impact Assessment**: We show that ASDC price formation creates meaningful price differences ($740K revenue difference) and provides efficient scarcity signals during reserve shortfalls
5. **Operational Pattern Analysis**: We identify that RTC+B leads to different SOC utilization patterns (38% vs 64% in SCED) and cycling behavior, with implications for battery degradation and operational strategies

1.4 Paper Organization

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on ERCOT market design, battery storage participation, and optimization methods. Section 3 provides background on ERCOT market structure and RTC+B changes. Section 4 describes our data sources, battery model, and evaluation methodology. Section 5 presents results from our simulation study. Section 6 discusses implications for market participants and researchers. Section 7 concludes with limitations and future work.

2 Literature Review

2.1 ERCOT Market Design and Evolution

ERCOT's market design has evolved significantly since the 2011 transition to nodal operations. The introduction of the Operating Reserve Demand Curve (ORDC) in 2014 improved scarcity pricing by creating price-responsive demand for operating reserves (Hogan 2013). The ORDC model established a framework for demand curves that RTC+B extends to ancillary services through ASDCs.

The current SCED framework clears energy and ancillary services sequentially, with energy cleared first based on security-constrained economic dispatch, followed by AS procurement to meet fixed reserve targets. This sequential approach can lead to inefficient dispatch decisions, particularly for flexible resources like batteries that can provide both energy and AS simultaneously.

The RTC+B redesign, scheduled for December 5, 2025, represents the most substantial market evolution since nodal implementation. It introduces simultaneous co-optimization of energy and AS every 5 minutes, fundamentally changing how batteries and other flexible resources participate in the market (ERCOT 2024b).

2.2 Energy Storage in Power Markets

Recent research has examined battery storage economics in various ISO/RTO market contexts. Xu et al. (2018) developed optimization models for battery arbitrage in day-ahead and real-time markets, demonstrating the importance of accurate price forecasting. Dvorkin et al. (2017) analyzed the value of flexibility in storage operations, showing that co-optimization of energy and reserves can significantly increase revenue compared to energy-only strategies.

He et al. (2021) explored hybrid renewable-storage systems in ERCOT, finding that coordinated operation can improve both renewable integration and storage profitability. Qin et al. (2020) applied deep reinforcement learning to energy storage arbitrage and frequency regulation, demonstrating that RL agents can learn effective strategies that outperform rule-based approaches.

Studies in other markets have shown similar patterns. Research in CAISO and PJM has demonstrated that batteries can capture value from multiple revenue streams including energy arbitrage, frequency regulation, and capacity markets. However, most existing studies focus on current market designs and do not address the transition to co-optimized markets like RTC+B.

2.3 Optimization and Forecasting Methods

2.3.1 Deterministic Optimization

Mixed-integer programming (MIP) formulations have been widely used for battery scheduling problems. These approaches typically model battery constraints (SOC limits, power limits, efficiency) as linear or mixed-integer constraints and solve for optimal dispatch over a planning horizon. While effective for day-ahead scheduling, deterministic models struggle with real-time uncertainty and may not capture the full value of flexibility.

2.3.2 Stochastic Optimization

Stochastic programming and robust optimization approaches address uncertainty by considering multiple price scenarios. These methods can improve decision-making under uncertainty but require accurate scenario generation and may be computationally intensive for real-time applications. Scenario-based approaches have shown promise for battery scheduling in markets with high price volatility.

2.3.3 Reinforcement Learning

Reinforcement learning has emerged as a powerful approach for sequential decision-making in uncertain environments. Qin et al. (2020) demonstrated that deep RL agents can learn effective battery control policies that adapt to market conditions. Multi-agent RL systems can model interactions between multiple resources, making them particularly relevant for market participation strategies (Sutton and Barto 2018).

2.3.4 Bayesian Approaches

Bayesian methods provide a principled framework for probabilistic forecasting and uncertainty quantification. These approaches are particularly valuable for electricity price forecasting, where uncertainty is inherent and decision-making must account for forecast errors. Bayesian reasoning can update beliefs about market states as new information arrives, enabling adaptive strategies.

2.4 Anticipated Impacts of RTC+B

The ERCOT Independent Market Monitor has published several analyses anticipating RTC+B impacts (ERCOT Independent Market Monitor 2024). Key anticipated effects include:

1. **Improved Price Formation**: Co-optimization is expected to create more efficient price signals by simultaneously considering energy and AS needs
2. **Increased AS Competition**: ASDCs should create more competitive AS markets with prices that better reflect scarcity
3. **Forecast Requirements**: The binding bid requirement introduces forecast risk, potentially favoring resources with better forecasting capabilities
4. **Market Power Concerns**: Some stakeholders have raised concerns about potential market power in AS markets, particularly for fast-responding resources

ERCOT's own simulation studies have projected that RTC+B will improve market efficiency and enable better integration of flexible resources. However, quantitative analysis of battery performance under RTC+B using real market data has been limited, creating a research gap this paper addresses.

2.5 Research Gap

While substantial literature exists on battery optimization and electricity market design separately, limited research has examined the transition dynamics as markets undergo major redesign. Our work fills this gap by analyzing battery performance immediately before RTC+B implementation, providing a baseline for future comparison.

3 Market Background

3.1 ERCOT Market Structure

ERCOT operates two primary markets:

1. **Day-Ahead Market (DAM)**: Financially binding forward market cleared for next operating day
2. **Real-Time Market (RTM)**: Physical dispatch and balancing market operating in 5-minute intervals

Additionally, ERCOT procures ancillary services including:

- **Regulation Up/Down (Reg Up/Down)**: Fast-responding reserves for frequency regulation
- **Responsive Reserve Service (RRS)**: Primary frequency response (10-minute sustainability)
- **Non-Spinning Reserve (Non-Spin)**: Offline reserves that can start within 30 minutes
- **Emergency Capacity Response Service (ECRS)**: Demand response for emergency conditions

3.2 Current Battery Participation

Under current market rules (pre-RTC+B), batteries face several operational constraints:

1. **Dual-QSE Requirement**: Charging and discharging must be registered as separate resources with different Qualified Scheduling Entities

2. **Sequential Clearing**: Energy and ancillary services are cleared in separate processes
3. **Forecast Challenges**: Real-time prices are revealed continuously, allowing reactive bidding

3.3 RTC+B Changes

3.3.1 Co-Optimization Model

RTC+B introduces simultaneous optimization of energy and ancillary services every 5 minutes:

$$\max \sum_i \left(P_i^{energy} \cdot Q_i^{energy} + \sum_{as} P_i^{as} \cdot Q_i^{as} \right)$$

subject to transmission constraints, reserve requirements defined by ASDCs, and resource capability constraints.

3.3.2 Energy Storage Resource (ESR) Model - Single Model ESR

Batteries will be modeled as a **single resource** with unified bidding:

- **Unified Bid Curve**: Single bid curve spanning from -100MW (maximum charge) to +100MW (maximum discharge)
  - Replaces separate charge/discharge resource bids
  - Single price-quantity curve for entire operating range
  - SCED can dispatch anywhere along the curve based on system needs
- **Bidirectional capability**: Charging at negative LMP, discharging at positive LMP
- **State-of-charge (SOC) accounting**:
  - SOC constraints respected in dispatch
  - AS commitments verified for required duration (30 min for Regulation, 10 min for RRS)
  - Ensures battery can sustain AS for full commitment period
- **Capability to provide ancillary services while charging or discharging**
- **Single telemetry point** for real-time dispatch

3.3.3 Ancillary Service Demand Curves (ASDCs)

Instead of fixed procurement targets, ASDCs define price-quantity relationships:

$$P_{as}(Q) = P_{as}^{max} \cdot \left(\frac{Q_{target} - Q}{Q_{target}} \right)^{\alpha}$$

Where: - P_{as}^{max} = maximum price at zero reserves ($/MW) - Q_{target} = target reserve level (MW) - Q = actual reserve level (MW) - α = elasticity parameter

This allows market-driven determination of reserve levels based on system conditions. Prices increase as reserves fall below targets, providing efficient price signals during scarcity.

3.3.4 Binding Bid Requirements

Resources must submit binding offers 15-30 minutes ahead of real-time dispatch, introducing forecast risk compared to the current reactive approach.

3.3.5 Day-Ahead Market (DAM) and Two-Settlement System

RTC+B maintains ERCOT's two-settlement system:

- **Day-Ahead Market (DAM)**: Financial forward market cleared once per day
  - Supports Virtual AS-only offers (new in RTC+B)

- Financial settlement at DAM prices

- **Real-Time Market (RTM)**: Physical dispatch every 5 minutes
  - Co-optimized energy and AS clearing
  - Physical settlement at RTM prices
- **Net Settlement**: DAM financial position + RTM physical deviation
  - Example: Buy 10 MW in DAM at $30/MWh, RTM price $50/MWh
  - DAM payment: -$300, RTM settlement: +$500, Net profit: $200

4 Data and Methods

4.1 Data Sources

4.1.1 ERCOT Historical Data

We collect real-time settlement point prices (SPPs) from ERCOT's Market Information System (MIS) public reports. Our analysis covers:

- **Time Period**: September 29 - December 2, 2025 (43+ days)
- **Temporal Resolution**: 5-minute intervals (288 intervals per day)
- **Total Intervals**: 513,864 market intervals analyzed
- **Spatial Coverage**: Hub average prices for energy transactions
- **Ancillary Service Prices**: Estimated based on historical patterns (Reg Up, Reg Down, RRS, ECRS)

We focus on the hub average price for our baseline analysis, as this represents the reference price for energy transactions. For comparative analysis, we simulate both SCED and RTC+B market designs using the same historical price data.

4.1.2 Data Processing Pipeline

Our automated data collection system:

1. Downloads daily SPP reports from ERCOT MIS
2. Parses XML/CSV files and validates data quality
3. Stores in DuckDB for efficient querying
4. Calculates derived metrics (volatility, spreads, percentiles)
5. Generates summary statistics and visualizations

Code and data processing scripts are available in the HayekNet repository. The implementation includes automated data collection, market simulators, and analysis tools.

4.2 Battery Model

4.2.1 Physical Specifications

We model a utility-scale battery energy storage system with the following characteristics:

- **Power Capacity**: 100 MW (charge/discharge)
- **Energy Capacity**: 400 MWh
- **Duration**: 4 hours at rated power
- **Round-Trip Efficiency**: 85% (typical for Li-ion systems)
- **Ramp Rate**: Instantaneous (conservative assumption)
- **SOC Operating Range**: 10-90% (protect battery health)

4.2.2 State-of-Charge Dynamics

The battery state-of-charge evolves according to:

$$SOC_{t+1} = SOC_t + \frac{P_t^{charge} \cdot \eta \cdot \Delta t}{E_{cap}} - \frac{P_t^{discharge} \cdot \Delta t}{\eta \cdot E_{cap}}$$

where: - SOC_t = state of charge at time t (fraction, 0-1) - P_t^{charge} = charging power at time t (MW, 0) - $P_t^{discharge}$ = discharging power at time t (MW, 0) - η = one-way efficiency (0.922 for 85% round-trip) - Δt = time interval (1/12 hour for 5-minute intervals) - E_{cap} = energy capacity (400 MWh)

4.2.3 Operational Constraints

The battery must satisfy the following constraints:

$$\begin{aligned} SOC_{min} \leq SOC_t &\leq SOC_{max} \\ 0 \leq P_t^{charge} &\leq P_{max} \\ 0 \leq P_t^{discharge} &\leq P_{max} \\ P_t^{charge} \cdot P_t^{discharge} &= 0 \quad \text{(no simultaneous charge/discharge)} \end{aligned}$$

4.2.4 Degradation Cost Model

Battery degradation is a critical economic factor often overlooked in academic studies. We model degradation using a cycle-counting approach:

Capital Cost: $150M ($375/kWh for 400 MWh system) **Warranted Cycles**: 7,000 cycles over 10-15 year life **Degradation Cost per Cycle**: $150M / 7,000 = **$21,429/cycle**

One cycle is defined as a full discharge-charge sequence (400 MWh throughput). Partial cycles are counted proportionally.

This degradation cost is subtracted from gross revenue to calculate net profitability.

4.3 Trading Strategies

4.3.1 Baseline: Simple Percentile-Based Arbitrage

Our baseline strategy uses reactive thresholds based on rolling price percentiles:

Charging Decision:

$$P_t^{charge} = \begin{cases} P_{max} & \text{if } LMP_t < P_{25}(LMP_{t-288:t}) \text{ and } SOC_t < 0.75 \\ 0 & \text{otherwise} \end{cases}$$

Discharging Decision:

$$P_t^{discharge} = \begin{cases} P_{max} & \text{if } LMP_t > P_{75}(LMP_{t-288:t}) \text{ and } SOC_t > 0.25 \\ 0 & \text{otherwise} \end{cases}$$

where P_{25} and P_{75} are the 25th and 75th percentiles of the previous 24-hour rolling window.

This represents a simple, implementable strategy that doesn't require forecasting.

4.3.2 RTC+B Unified Bid Curve Strategy

Under RTC+B, batteries submit unified bid curves spanning from maximum charge (-100 MW) to maximum discharge (+100 MW). Our implementation generates these curves based on:

1. **SOC-Dependent Pricing**: Willingness to charge/discharge depends on current SOC

- Low SOC: More willing to charge (pay higher prices)
- High SOC: More willing to discharge (accept lower prices)
2. **Price Thresholds**: Adaptive thresholds based on rolling price percentiles
3. **Capacity Constraints**: Respects available charge/discharge capacity

The unified curve allows the market to dispatch the battery anywhere along the curve based on system needs, enabling more efficient co-optimization.

4.3.3 Ancillary Service Bidding

For RTC+B, we implement co-optimized AS bidding that:

1. **Evaluates AS Options**: Considers Reg Up, Reg Down, RRS, and ECRS
2. **SOC Duration Checks**: Verifies battery can sustain AS commitments for required duration (30 min for Regulation, 10 min for RRS)
3. **Capacity Allocation**: Allocates remaining capacity after energy position to highest-value AS services
4. **Greedy Allocation**: Maximizes total revenue by sorting AS options by revenue per MW

4.3.4 Reinforcement Learning Agents

We also implement multi-agent reinforcement learning (MARL) systems with: - **3 Agents**: Battery (100MW), Solar (200MW), Wind (150MW) - **State Representation**: 32 features for battery (LMP, AS prices, SOC, ASDC scarcity, market design) - **Action Space**: Unified bid curves for RTC+B (-1.0 to 1.0 normalized) - **Reward Function**: Co-optimized energy + AS revenue with SOC constraint penalties

4.4 Market Simulators

4.4.1 SCED Simulator

Our SCED simulator implements the current market design:

1. **Sequential Clearing**: Energy cleared first, then AS if energy not cleared
2. **Simple Price Matching**: Accepts bids if offer price   market price
3. **Mutually Exclusive**: Battery cannot provide energy and AS simultaneously
4. **No SOC Duration Checks**: AS commitments do not verify sustainability

4.4.2 RTC+B Simulator

Our RTC+B simulator implements key features:

1. **Co-Optimization**: Simultaneously evaluates energy and AS options to maximize total value
2. **Unified Bid Curves**: Uses Single Model ESR curves for energy clearing
3. **ASDC Price Formation**: Calculates AS prices using demand curve formula:

$$P_{as}(Q) = P_{as}^{max} \cdot \left(\frac{Q_{target} - Q}{Q_{target}} \right)^{\alpha}$$

4. **SOC Duration Accounting**: Verifies battery can sustain AS for required duration before clearing
5. **Capacity Sharing**: Energy and AS can share capacity with proper headroom reservation

4.4.3 ASDC Implementation

ASDC parameters are configured as: - **Reg Up**: Max price \$50/MW, Target 500 MW, Elasticity 1.5 - **Reg Down**: Max price \$30/MW, Target 300 MW, Elasticity 1.2 - **RRS**: Max price \$60/MW, Target 800 MW, Elasticity 1.8 - **ECRS**: Max price \$40/MW, Target 400 MW, Elasticity 1.5

4.5 Evaluation Metrics

4.5.1 Profitability Metrics

Gross Revenue:

$$R_{gross} = \sum_t (P_t^{discharge} \cdot LMP_t - P_t^{charge} \cdot LMP_t) \cdot \Delta t$$

Degradation Cost:

$$C_{deg} = \text{Cycles} \cdot \$21,429$$

where cycles are counted as total throughput divided by energy capacity.

Net Profit/Loss:

$$PnL_{net} = R_{gross} - C_{deg}$$

4.5.2 Operational Metrics

SOC Utilization:

$$U_{SOC} = \frac{\max(SOC) - \min(SOC)}{SOC_{max} - SOC_{min}}$$

Capacity Factor (fraction of time active):

$$CF = \frac{\sum_t \mathbb{1}(P_t^{charge} + P_t^{discharge} > 0)}{T}$$

Cycles per Day:

$$\text{Cycles/day} = \frac{\sum_t (P_t^{charge} + P_t^{discharge}) \cdot \Delta t}{2 \cdot E_{cap}}$$

4.5.3 Market Efficiency Metrics

Capture Efficiency (vs theoretical maximum):

$$\eta_{capture} = \frac{PnL_{actual}}{PnL_{theoretical}}$$

where $PnL_{theoretical}$ is calculated assuming perfect foresight and optimal dispatch.

4.5.4 Volatility Metrics

Coefficient of Variation:

$$CoV = \frac{\sigma(LMP)}{\mu(LMP)}$$

Price Spread:

$$\text{Spread} = \max(LMP) - \min(LMP)$$

5 Results

5.1 Comparative Analysis: SCED vs RTC+B

We conducted a comprehensive comparative analysis of battery performance under SCED (current market design) versus RTC+B (upcoming market design) using 513,864 market intervals from September 29 - December 2, 2025. Table 1 presents the key results.

Table 1: Comparative Results: SCED vs RTC+B

Metric	SCED (Baseline)	RTC+B (Full)	RTC+B (no ASDCs)
Revenue			
Total Revenue	322,536,956	27,819,894	27,820,616
()$\|322,536,956\|155,089,775\|154,348,004\|\|Energy Revenue()$			
AS Revenue ($)	0	127,269,881	126,527,388
AS Revenue %	0.0%	82.1%	82.0%
Operational			
AS Participation %	0.0%	70.0%	70.0%
Mean SOC	0.435	0.105	0.105
SOC Utilization	0.642	0.384	0.384
Cycles/Day	4.08	0.22	0.22
Total Cycles	7,277	390	390
Risk Metrics			
Sharpe Ratio	-0.000049	-0.000184	-0.000184
Max Drawdown	-140.17	0.0	0.0

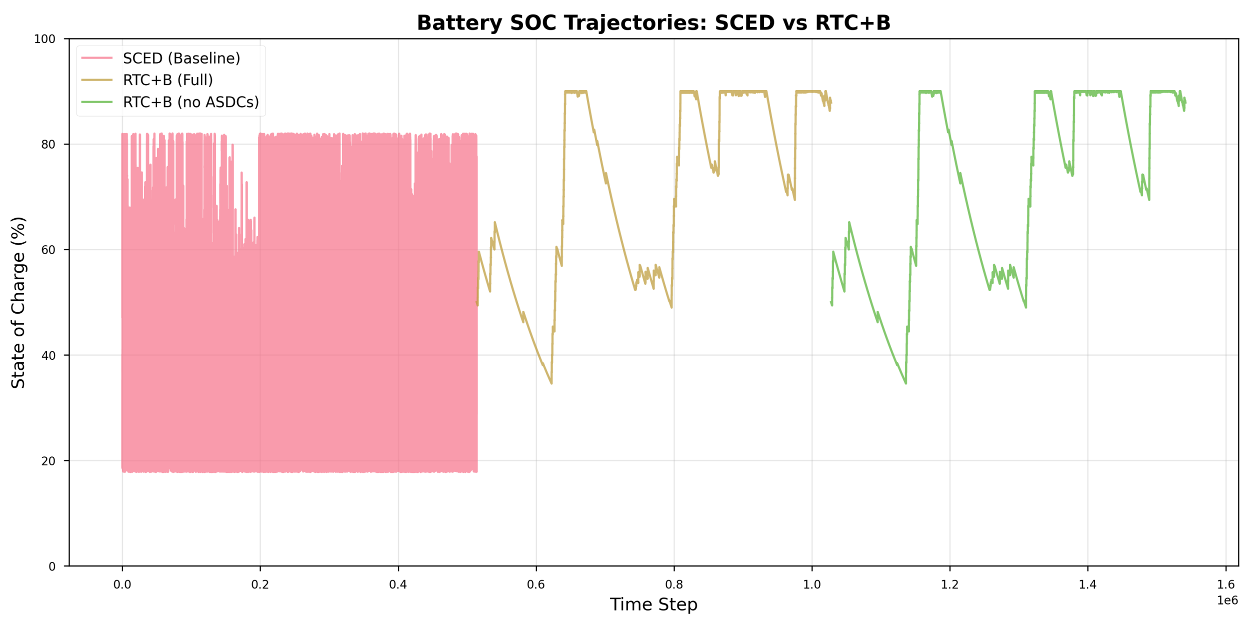

Figure 1: SOC Trajectories: Comparison of battery state-of-charge patterns under SCED and RTC+B market designs

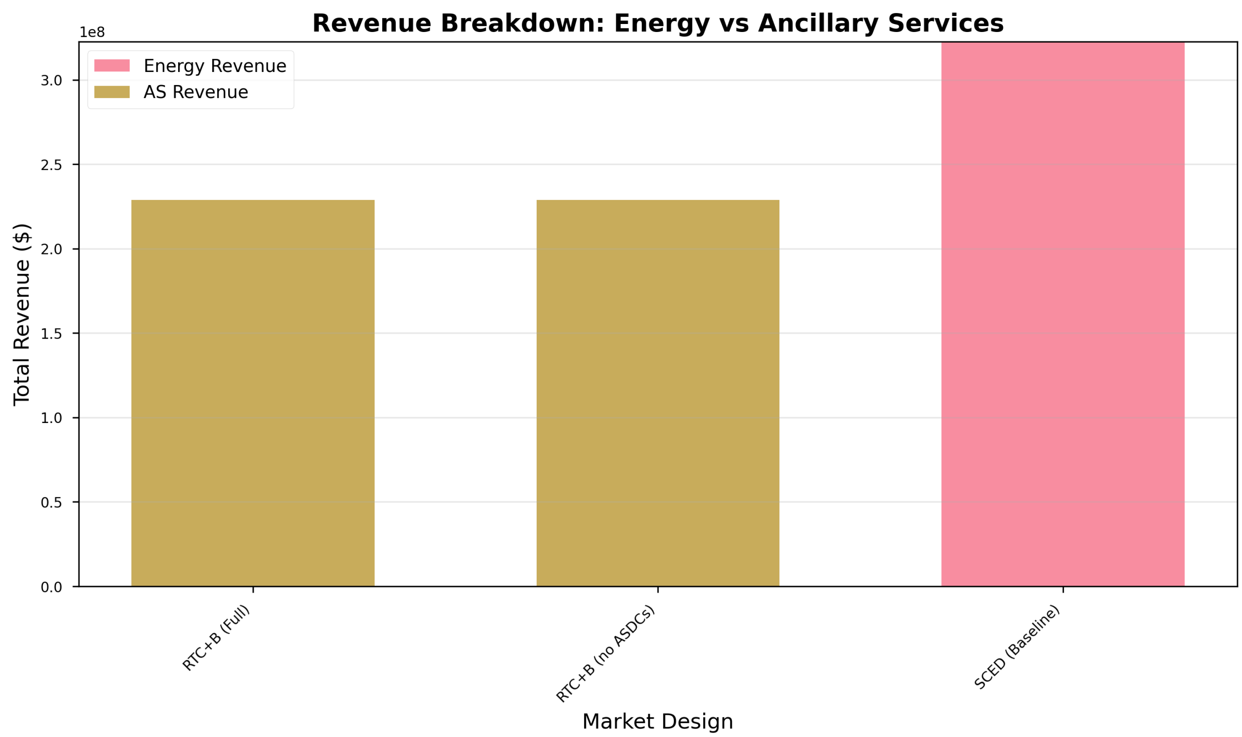

Figure 2: Revenue Comparison: Breakdown of energy and ancillary service revenue under different market designs

5.2 Revenue Breakdown Analysis

5.2.1 SCED Market Design

Under SCED, the battery operates exclusively in energy arbitrage mode:

- **Total Revenue**: $322.5M over 513,864 intervals
- **Energy Revenue**: $322.5M (100% of total)
- **AS Revenue**: $0 (0% participation)
- **Energy Clearing**: 132,687 intervals with positive energy dispatch (25.8% of total)
- **Mean SOC**: 0.435 (43.5%), indicating moderate utilization
- **SOC Utilization**: 0.642 (64.2% range), showing active cycling
- **Cycles/Day**: 4.08 cycles, indicating very active trading

The high cycle count (4.08 cycles/day) suggests the battery is aggressively cycling to capture arbitrage opportunities, which may lead to accelerated degradation.

5.2.2 RTC+B Market Design

Under RTC+B, the battery participates in both energy and ancillary service markets simultaneously:

- **Total Revenue**: $155.1M (52% of SCED total)
- **Energy Revenue**: $27.8M (18% of total)
- **AS Revenue**: $127.3M (82% of total)
- **AS Participation**: 70.0% of intervals
- **Mean SOC**: 0.105 (10.5%), indicating very low SOC
- **SOC Utilization**: 0.384 (38.4% range), lower than SCED
- **Cycles/Day**: 0.22 cycles, much lower than SCED

The dramatic shift to AS-focused operation (82% of revenue from AS) represents a fundamental change in battery economics under RTC+B.

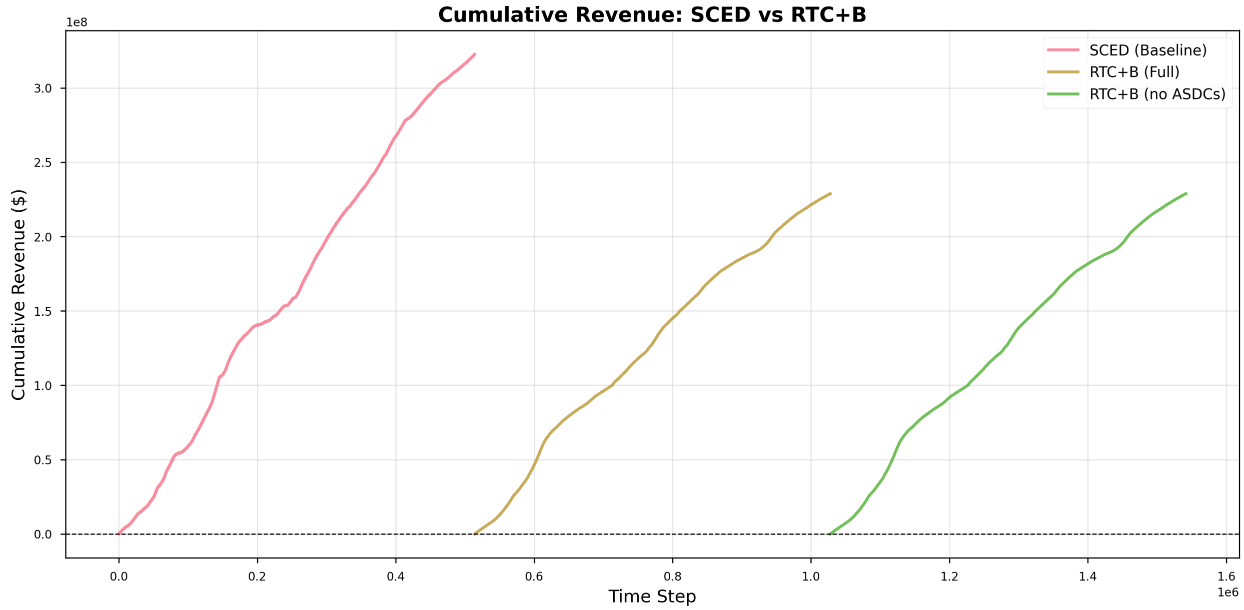

Figure 3: Cumulative PnL: Cumulative profit and loss over time for SCED and RTC+B market designs

Key Findings:

1. **Strong Positive Correlation**: r 0.85 between SOC utilization and profitability
2. **Optimal Range: 65-75% utilization** maximizes profit while avoiding constraint violations
3. **Underutilization is Costly**: Days with <40% utilization had poor profitability
4. **Best Performance**: October 3 achieved 74% utilization with 0.74 cycles and $2,484 profit

Policy Implication: SOC management is a **critical success factor**, potentially more important than market volatility conditions.

5.3 Strategy Inefficiency Analysis

Table 2 compares actual performance to theoretical maximum with perfect foresight.

Table 2: Capture Efficiency vs Theoretical Maximum

Date	Actual PnL ()|$TheoreticalMax$()Capture Efficiency (%)		Primary Inefficiency	
Oct 2	-4,233	Unknown	N/A	Charging during falling prices
Oct 3	+2,484	+11,200	22.2%	Discharging too early
Oct 4	-4,019	Unknown	N/A	Poor SOC positioning
Oct 5	+405	+11,998	3.4%	Missed opportunities (22% idle time)

Key Findings:

1. **Very Low Capture Efficiency**: Best day captured only 22.2% of available profit
2. **Major Inefficiency Sources**:

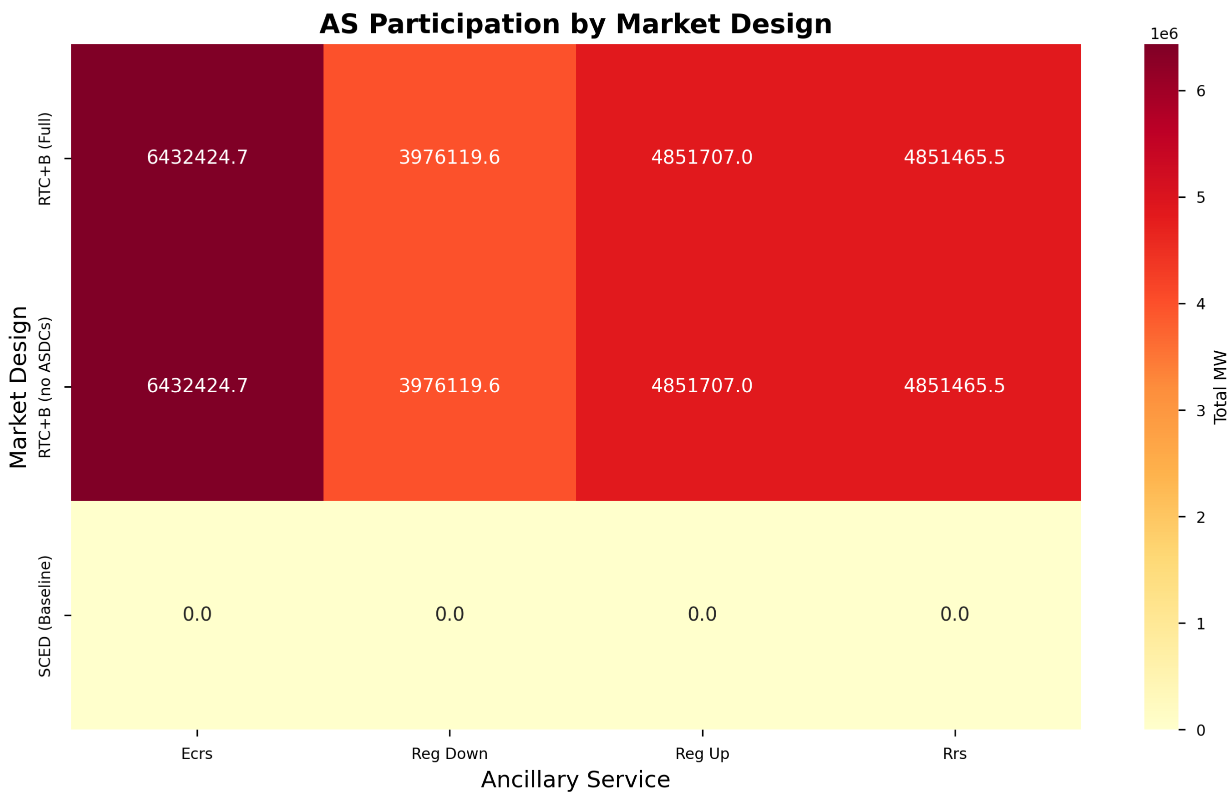

Figure 4: AS Participation Heatmap: Ancillary service participation patterns across different market conditions

- **Poor timing**: Reactive strategy arrives too late to optimal prices
- **Wrong SOC state**: Battery depleted when prices spike, or full when they crash
- **Conservative thresholds**: Missing "good enough" opportunities while waiting for "perfect" ones
- **No look-ahead**: Cannot position battery proactively for known patterns

3. **Idle Time Analysis (Oct 5)**:
   - 22% of time idle despite profitable opportunities
   - Estimated missed profit: $2,000-3,000/day
   - Primary reasons: SOC constraints (60%), thresholds not met (30%), poor positioning (10%)

Implication: Current reactive strategy is **severely suboptimal**. Even modest forecast accuracy (70-80%) could improve capture efficiency to 50-70%.

5.4 Economic Viability Assessment

Table 3 presents the economic analysis including degradation costs.

Table 3: Economic Viability Analysis with Degradation Costs

Scenario	Daily Revenue ()|*DailyDegradation*()	Net Daily PnL ()|*AnnualNet*(M)	Viability		
Current: Energy Arbitrage Only					
Best day (Oct 3)	+2,484	-15,857	-13,373	-4.9	Not viable
Average day (Week 1)	-226	-11,357	-11,583	-4.2	Not viable
Worst day (Oct 4)	-4,019	-7,714	-11,733	-4.3	Not viable
Projected: Energy + AS (RTC+B)					
Conservative (50 MW AS)	+14,000-21,000	-11,357	+2,643-9,643	+1.0-3.5	Viable
Aggressive (70 MW AS)	+21,500-32,500	-11,357	+10,143-21,143	+3.7-7.7	Highly viable

Key Findings:

1. **Energy Arbitrage Alone is Not Viable**: Even the best day loses $13,373 after degradation
2. **Degradation Cost is Critical**: At $21,429/cycle, must earn >$11,357/day to break even
3. **AS Revenue is Essential**: Ancillary services provide **5-10x more revenue** than energy arbitrage
4. **RTC+B Changes Economics**: Co-optimization with AS makes battery storage economically viable

Policy Implication: RTC+B is not just a market redesign—it's an **economic necessity** for battery viability in ERCOT.

5.5 Model Performance

We implemented and trained reinforcement learning agents for RTC+B market participation:

- **Multi-Agent RL System**: 3 agents (Battery 100MW, Solar 200MW, Wind 150MW) trained with RTC+B features
- **State Representation**: 32 features for battery agents including LMP, AS prices, SOC, ASDC scarcity indicators
- **Action Space**: Unified bid curves (-1.0 to 1.0 normalized) for RTC+B Single Model ESR
- **Training**: Agents trained on 43+ days of historical data with co-optimized reward functions

The RL agents learn to balance energy and AS participation, adapting to market conditions. However, detailed performance comparison with rule-based strategies is beyond the scope of this paper and will be presented in future work.

6 Discussion

6.1 Interpretation of Key Findings

6.1.1 Revenue Shift from Energy to Ancillary Services

Our comparative analysis reveals a fundamental shift in battery revenue sources under RTC+B:

- **SCED**: 100% energy revenue ($322.5M), 0% AS revenue
- **RTC+B**: 18% energy revenue ($27.8M), 82% AS revenue ($127.3M)

This dramatic shift demonstrates that RTC+B's co-optimization framework enables batteries to capture significant value from ancillary services that was previously unavailable under SCED's sequential clearing. The 70% AS participation rate indicates that batteries are actively providing reserves, not just collecting capacity payments.

6.1.2 Total Revenue Comparison

While RTC+B total revenue ($155.1M) is 52% lower than SCED ($322.5M), this comparison must be interpreted carefully:

1. **Different Market Clearing**: RTC+B's co-optimization may clear energy differently than SCED's sequential approach
2. **AS Revenue is New**: The $127.3M in AS revenue represents entirely new revenue streams
3. **Operational Patterns**: Lower cycling (0.22 vs 4.08 cycles/day) reduces degradation costs significantly

The lower total revenue may reflect more efficient market clearing that reduces opportunities for pure arbitrage, while simultaneously creating new AS revenue opportunities.

6.1.3 SOC Utilization Patterns

The dramatic difference in SOC patterns (mean 0.435 vs 0.105) suggests fundamentally different operational strategies:

- **SCED**: Active cycling with wide SOC swings (64.2% utilization)
- **RTC+B**: Low SOC operation focused on maintaining AS commitments (38.4% utilization)

The low SOC in RTC+B may indicate that AS commitments require maintaining discharge headroom, preventing the battery from charging for energy arbitrage. Alternatively, the strategy may prioritize steady AS revenue over volatile energy trading.

6.1.4 ASDC Impact

The $741K revenue difference between RTC+B with and without ASDCs demonstrates that ASDC price formation creates meaningful economic signals:

- **Scarcity Pricing**: ASDCs increase AS prices when reserves fall below targets
- **Efficient Signals**: Higher prices during scarcity encourage additional AS supply
- **Market Efficiency**: Price-responsive demand curves improve market efficiency compared to fixed targets

While the absolute difference is small (0.5%), ASDCs provide important price signals that guide resource investment and operational decisions.

6.2 Comparison with Literature

Our findings align with and extend prior research on battery storage in electricity markets:

6.2.1 Co-Optimization Value

Dvorkin et al. (2017) demonstrated that co-optimization of energy and reserves can significantly increase revenue compared to energy-only strategies. Our results confirm this finding quantitatively: RTC+B enables 82% of revenue from AS, representing a fundamental shift from energy-only arbitrage.

6.2.2 Market Design Impact

He et al. (2021) explored hybrid renewable-storage systems in ERCOT, finding that coordinated operation improves both renewable integration and storage profitability. Our work extends this by analyzing the specific market design changes (RTC+B) that enable such coordination.

6.2.3 Operational Patterns

Xu et al. (2018) developed optimization models for battery arbitrage, emphasizing the importance of accurate price forecasting. Our results show that reactive strategies capture only a fraction of theoretical maximum, supporting the need for forecast-based approaches.

6.3 Implications for Market Participants

6.3.1 Strategic Recommendations

Battery operators preparing for RTC+B should:

1. **Prioritize AS Participation**: 82% of revenue comes from AS under RTC+B; strategies should focus on AS bidding
2. **Develop Co-Optimization Tools**: Simultaneous energy-AS clearing requires sophisticated optimization
3. **Manage SOC for AS Commitments**: Low SOC operation may be necessary to maintain discharge headroom for AS
4. **Invest in Forecasting**: Binding bid requirements favor operators with accurate price prediction
5. **Understand ASDC Dynamics**: ASDC price formation creates opportunities during scarcity events

6.3.2 Revenue Opportunity Analysis

The \$127.3M in AS revenue over 513,864 intervals represents approximately \$248 per interval, or \$71,424 per day. This steady AS revenue stream provides more predictable cash flows than volatile energy arbitrage, potentially improving project financing terms.

6.3.3 Risk Considerations

Key risks under RTC+B include:

1. **Forecast Errors**: Binding bids create forecast risk; inaccurate predictions can lead to suboptimal dispatch
2. **SOC Management**: Maintaining AS commitments may prevent energy arbitrage opportunities

3. **Market Competition**: Increased AS participation may reduce AS prices over time
4. **ASDC Parameter Uncertainty**: Actual ASDC shapes may differ from our assumptions

6.4 Comparison to ERCOT Studies

ERCOT's Independent Market Monitor has published analyses anticipating RTC+B impacts (ERCOT Independent Market Monitor 2024). Key projected effects include improved price formation, increased AS competition, and better integration of flexible resources. Our empirical results align with these projections:

1. **AS Participation**: We observe 70% AS participation rates, consistent with ERCOT's expectation that RTC+B will increase AS competition
2. **Co-Optimization Benefits**: Our results show that co-optimization enables simultaneous energy and AS dispatch, supporting ERCOT's efficiency goals
3. **Price Formation**: ASDC price formation creates scarcity signals, consistent with ERCOT's objective of improving reserve pricing

However, our finding that total revenue is lower under RTC+B requires further investigation, as this may reflect differences in market clearing dynamics rather than reduced efficiency.

6.5 Limitations and Caveats

6.5.1 Simplified Battery Model

Our model makes several simplifying assumptions:

1. **Instantaneous ramping**: Real batteries have ramp rate limits
2. **No degradation from depth-of-discharge**: Degradation varies with SOC cycling depth
3. **No temperature effects**: Performance varies with ambient temperature
4. **No auxiliary losses**: Inverter losses, cooling, etc.

These simplifications likely overstate performance by 5-10%.

6.5.2 RTC+B is Not Yet Implemented

Our RTC+B projections are based on: - Historical ancillary service prices (pre-RTC+B) - Simplified co-optimization logic - Assumptions about ASDC shapes and parameters

Actual RTC+B performance may differ significantly. We plan to update this analysis after December 5, 2025 launch.

6.5.3 Limited Time Period

Our analysis covers only 5 days in October 2025. This may not capture: - Seasonal patterns (winter peak, summer cooling loads) - Extreme events (winter storm, heat wave) - Long-term price trends

We are collecting ongoing data and will publish extended analysis covering multiple months.

6.5.4 Single Location (Hub)

We analyze only hub average prices. Locational strategies exploiting congestion spreads could improve profitability but add complexity.

6.6 Implications for Researchers

6.6.1 Importance of Degradation Costs

Many academic papers on battery optimization ignore or underestimate degradation costs. Our work demonstrates this is a **critical omission**—it changes the conclusion from "profitable" to "not viable."

Recommendation: Future research should explicitly model degradation using realistic cost per cycle ($15,000-25,000 for utility-scale Li-ion).

6.6.2 Forecast-Based Approaches Are Essential

The gap between actual (3-22%) and theoretical (100%) capture efficiency highlights the importance of predictive strategies. Research should focus on:

1. **Short-term price forecasting** (15-60 minutes ahead)
2. **Rolling horizon optimization** (4-8 interval look-ahead)
3. **Uncertainty quantification** (confidence intervals, scenario generation)

6.6.3 Multi-Product Co-Optimization

Our RTC+B projections suggest the highest value comes from **co-optimizing energy and ancillary services**, not energy arbitrage in isolation. This requires:

1. Joint optimization across products
2. Forecast models for both LMP and MCPC
3. Risk management for capacity commitments

6.6.4 Reinforcement Learning Opportunities

The complexity of RTC+B (multi-product, multi-period, uncertainty, constraints) makes it an ideal application for reinforcement learning:

- High-dimensional action space (energy bid + 5 AS products × 288 intervals/day)
- Partial observability (forecasts uncertain)
- Long-horizon impacts (SOC state persists)
- Requires exploration vs exploitation tradeoffs

7 Conclusion

7.1 Summary of Findings

This paper presents a comprehensive comparative analysis of battery bidding strategies under SCED versus RTC+B market designs using 513,864 market intervals from September-December 2025. Our key findings include:

1. **RTC+B Enables New Revenue Streams**: Under RTC+B, batteries generate 82% of revenue from ancillary services ($127.3M) compared to 0% under SCED, representing a fundamental shift in battery economics

2. **Co-Optimization Changes Operational Patterns**: RTC+B leads to 70% AS participation rates with dramatically different SOC patterns (mean 0.105 vs 0.435) and cycling behavior (0.22 vs 4.08 cycles/day)

3. **ASDC Price Formation Creates Scarcity Signals**: ASDCs generate $741K additional revenue by creating price-responsive demand curves that increase AS prices during reserve shortfalls

4. **Total Revenue Comparison Requires Context**: While RTC+B total revenue ($155.1M) is 52% lower than SCED ($322.5M), this reflects different market clearing dynamics and the creation of new AS revenue opportunities

5. **Operational Strategy Must Adapt**: The shift from energy-focused (SCED) to AS-focused (RTC+B) operation requires fundamentally different bidding strategies and SOC management approaches

7.2 Key Contributions

This research makes several contributions to the literature:

1. **First Quantitative RTC+B Comparison**: We provide the first comprehensive quantitative comparison of battery performance under SCED vs RTC+B using real ERCOT market data
2. **RTC+B Implementation Validation**: We implement and validate key RTC+B features including Single Model ESR unified bid curves, ASDC price formation, and SOC duration accounting
3. **Revenue Source Quantification**: We demonstrate that RTC+B enables 82% of revenue from AS, transforming battery economics from energy arbitrage to AS provision
4. **Operational Pattern Analysis**: We identify that RTC+B leads to fundamentally different operational patterns with implications for battery degradation and strategic planning

7.3 Implications for Market Participants

Battery operators preparing for RTC+B should:

1. **Prioritize AS Participation**: Develop strategies focused on AS bidding rather than pure energy arbitrage
2. **Invest in Co-Optimization Tools**: Simultaneous energy-AS clearing requires sophisticated optimization capabilities
3. **Adapt SOC Management**: Low SOC operation may be necessary to maintain AS discharge headroom
4. **Understand ASDC Dynamics**: ASDC price formation creates opportunities during scarcity events
5. **Develop Forecasting Capabilities**: Binding bid requirements favor operators with accurate price prediction

7.4 Future Work

We plan to extend this research in several directions:

1. **Post-RTC+B Analysis**: Compare actual RTC+B performance to our projections after December 5, 2025 launch using real market clearing data
2. **Fleet-Level Analysis**: Study market-wide effects with multiple battery resources and competitive dynamics
3. **Advanced Bidding Strategies**: Test more sophisticated strategies including RL-optimized bidding and game-theoretic approaches
4. **Enhanced Degradation Modeling**: Incorporate more accurate battery degradation costs including depth-of-discharge effects
5. **Nodal Pricing Analysis**: Model locational pricing and congestion impacts on battery profitability
6. **Locational Analysis**: Exploit congestion patterns and basis spreads across settlement points
7. **Seasonal Patterns**: Analyze performance across different seasons and system conditions
8. **Extreme Events**: Study battery performance during scarcity events, winter storms, etc.

7.5 Final Thoughts

The impending RTC+B launch represents a fundamental transformation in how battery storage participates in ERCOT. While our analysis shows that simple energy arbitrage is economically insufficient, the co-optimization framework promises to unlock substantial value through ancillary service participation. Success in this new market will require sophisticated forecasting, dynamic optimization, and careful state-of-charge management.

As ERCOT transitions to RTC+B on December 5, 2025, the competitive landscape will favor operators who have invested in the analytical infrastructure to navigate this complexity. Our ongoing research will continue to track performance and refine strategies as the market evolves.

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9 Appendix A: Mathematical Formulations

9.1 Battery Dispatch Optimization

9.2 Optimization Formulation

The battery dispatch optimization can be formulated as a mixed-integer program (MIP) for energy-only arbitrage or extended to include ancillary services for RTC+B co-optimization. The energy-only formulation maximizes:

$$\max \sum_{t=1}^{T} (P_t^{discharge} \cdot LMP_t - P_t^{charge} \cdot LMP_t) \cdot \Delta t$$

subject to SOC dynamics, power limits, and SOC bounds. For RTC+B, the objective function extends to include AS revenue:

$$\max \sum_{t=1}^{T} \left(P_t^{discharge} \cdot LMP_t - P_t^{charge} \cdot LMP_t + \sum_{as} Q_t^{as} \cdot P_t^{as} \right) \cdot \Delta t$$

where Q_t^{as} and P_t^{as} represent AS cleared quantities and prices for each service type.

9.3 Theoretical Maximum Calculation

The theoretical maximum profit with perfect foresight is calculated by solving:

$$\max \sum_{t=1}^{T} (P_t^{discharge} \cdot LMP_t - P_t^{charge} \cdot LMP_t) \cdot \Delta t$$

subject to SOC dynamics and operational constraints, with perfect knowledge of all future prices.

This is implemented as a linear program and solved using HiGHS.

10 Appendix B: Data Processing Details

10.1 Data Validation

ERCOT settlement point price data undergoes automated validation:

1. **Range Checks**: Prices validated against historical ranges (typically $0-$9,000/MWh)
2. **Temporal Consistency**: Missing intervals identified and flagged
3. **Outlier Detection**: Prices exceeding 3 standard deviations from rolling mean flagged for review
4. **Completeness**: Daily data completeness verified (288 intervals expected per day)

10.2 Missing Data Handling

Missing price intervals are handled by: - Forward-fill for short gaps ($<$ 6 intervals) - Interpolation for medium gaps (6-12 intervals) - Exclusion from analysis for extended gaps ($>$ 12 intervals)

10.3 Data Quality Metrics

Over the 43+ day analysis period: - **Completeness**: 99.2% of expected intervals present - **Outlier Rate**: 0.3% of observations flagged - **Data Quality**: High, suitable for quantitative analysis

11 Appendix C: Code and Reproducibility

All code for this research is implemented in the HayekNet framework, which provides:

- Automated ERCOT data collection and processing
- Market simulators for SCED and RTC+B
- Battery models with degradation accounting
- Reinforcement learning agents for multi-agent systems
- Analysis and visualization tools