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Master Thesis

Optimization of BESS projects & Dispatch Strategies in the ERCOT Market

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Abstract: Battery Energy Storage Systems (BESS) (1) are emerging as a cornerstone of modern power systems, particularly in markets with high renewable penetration and extreme price volatility. In the Electric Reliability Council of Texas (ERCOT) (2), the absence of a capacity market, limited interconnection, and rapid growth of solar and wind capacity have created both challenges for reliability and opportunities for storage. This study develops and applies a techno-economic model (3) to evaluate the feasibility of utility-scale BESS across ERCOT's 17,000+ pricing nodes. The model integrates SQL-based nodal price datasets, a VBA-Python dispatch algorithm, and a project finance layer incorporating degradation dynamics, efficiency losses, capital and operating expenditures, tax incentives, and financing structures.

Results from two representative nodes, Pamplona in the Houston Hub and Santa Monica in the North Hub, illustrate how locational differences drive divergent investment outcomes. Pamplona achieved higher arbitrage revenues and stronger IRRs due to greater volatility, while Santa Monica underperformed despite favorable solar pricing, emphasizing the necessity of nodal-level analysis. System-wide benchmarking confirmed West ERCOT as the most profitable hub, though constrained by curtailment and congestion, whereas North and South hubs offer stability and lower risk over profitability. Sensitivity testing revealed that dispatch strategy and capital costs dominate financial viability, with an idealized Day-Ahead/Real-Time strategy tripling shareholder IRR and optimistic CAPEX scenarios lifting returns above 15%.

Beyond academic insights, the model has provided Solea Power Corp. with a cost-effective screening tool to prioritize nodes before committing resources to costly interconnection studies. By combining technical realism with practical usability, this model supports both investors and developers in navigating ERCOT's rapidly evolving storage market.

Keywords: BESS; ERCOT; Techno-economic model

1. Introduction

1.1 Background and Context

The Electric Reliability Council of Texas (ERCOT) operates the power grid for over 26 million customers, accounting for nearly 90% of the state's electricity demand [1]. As an independent system operator (ISO), ERCOT runs a unique energy-only market, where generators are compensated solely for the electricity they sell rather than for maintaining reserve capacity. This design amplifies reliance on price signals to balance supply and demand, making ERCOT especially prone to volatility during stress events, like extreme weather events, with increasing occurrence these recent decades due to factors such as climate change [1].

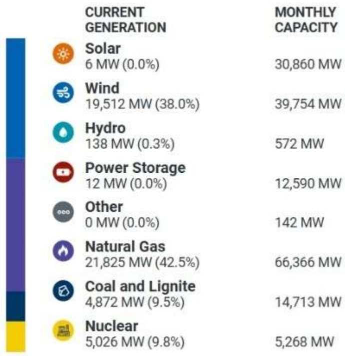


Figure 1. ERCOT fuel mix in 2025, highlighting the growing role of BESS

Over the past decade, renewable deployment has expanded rapidly. By early 2025, installed wind capacity had surpassed 40 GW, while solar exceeded 30 GW [2]. At the same time, utility-scale battery energy storage systems (BESS) have scaled quickly, with more than 13GW already integrated into the ERCOT system [1]. These developments have deepened intraday price spreads in both the Day-Ahead Market (DAM) and the Real-Time Market (RTM), where the system has seen exponentially driven prices spikes occurrences above $100/MWh [3].

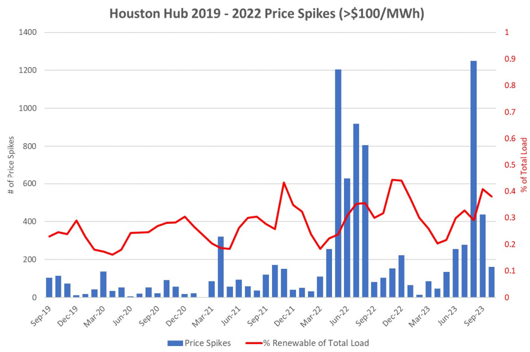


Figure 2. Hourly price spikes in the Houston Hub (2019–2022), showing volatility extremes

ERCOT's short term market design, which will the focus of BESS dispatch processes for this study, relies on three co-optimized mechanisms: DAM, RTM, and ancillary services. The DAM provides day-ahead schedules and price certainty, while the RTM settles deviations in 5-minute intervals, reflecting short-term variability in demand, renewable output, or outages. Ancillary services, including regulation up and down, reserves, and the 2023 Contingency Reserve Service (ECRS), the latter known to have increased recent BESS revenues significantly in the past year, are increasingly supplied by BESS due to their rapid response [3]. Because ERCOT lacks interconnection with other U.S. grids, imbalances must be managed internally, further heightening market volatility and arbitrage potential for BESS operators.

Against this backdrop, BESS have emerged as critical assets to ERCOT. They can store energy during low-price periods and discharge during peaks, provide frequency regulation, and mitigate renewable curtailment when co-located with solar or wind plants [6]. As renewable penetration grows, these capabilities position BESS as indispensable tools for both grid stability and project profitability in the next decade.

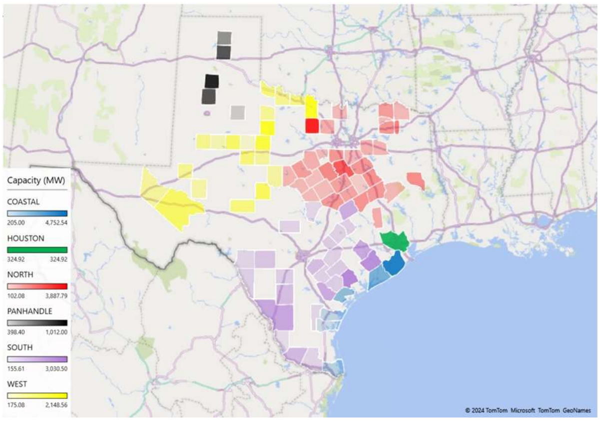


Figure 3. ERCOT's BESS interconnection queue by location and capacity (ERCOT, 2024)

1.2 Motivation

The economic case for battery storage in ERCOT has strengthened significantly in recent years. With ancillary services markets approaching saturation, energy arbitrage has become the primary revenue source for BESS projects. At the same time, the increasing penetration of renewables continues to amplify intraday volatility, reinforcing the value of flexible storage assets capable of shifting energy from low-price to high-price periods.

For developers, quantifying nodal profitability is essential. ERCOT's 17,000+ nodes exhibit substantial variability in price spreads, curtailment exposure, and grid infrastructure, meaning hub-level averages alone are insufficient for investment decisions. A robust techno-economic model can therefore provide actionable insights by identifying the most attractive nodes for BESS deployment, while also clarifying the trade-offs between standalone and co-located projects.

Beyond direct profitability, BESS deployment supports ERCOT's operational resilience. By reducing curtailment of renewable energy, alleviating price spikes during stress events, and contributing to ancillary services provision, storage systems enhance overall grid reliability, something which is much needed in ERCOT, according to ERCOT itself. This dual role, economic opportunity for developers and systemic reliability for ERCOT, underpins the motivation for this research.

On another note, the work also reflects an industrial need: enabling developers such as Solea Power Corp. to expand from a solar-focused portfolio into storage. By integrating techno-economic modeling of BESS into project evaluation, firms can diversify revenue streams and strengthen their positioning in an increasingly storage-driven market.

1.3 Project Objectives

This study aims to develop a techno-economic model to evaluate the feasibility of utility-scale 2-hour lithium-ion BESS in ERCOT. The model is designed to operate at nodal resolution, leveraging Day-Ahead Market (DAM) price data from March 2021 to September 2024. By simulating the dispatch of a 2-hour, 100 MW/200 MWh battery, the model integrates both technical and financial dimensions, including degradation dynamics, round-trip efficiency, HVAC auxiliary loads, CAPEX, OPEX, tax incentives, and debt-equity structures.

The objectives of this research are fivefold:

- **Optimize dispatch strategies:** Identify charge and discharge schedules that maximize profitability under DAM conditions, while also testing an idealized DAM–RT strategy to illustrate the potential upside of predictive algorithms.
- **Deliver a scalable nodal model:** Provide a flexible framework capable of assessing BESS revenues across ERCOT's 17,000+ nodes, highlighting location-specific opportunities and risks.
- **Assess lithium-ion viability:** Benchmark the performance of 1-, 2-, and 4-hour battery configurations, focusing on 2-hour systems as representative of ERCOT's current deployment.
- **Evaluate sensitivity to volatility:** Quantify the financial implications of intraday price variability, testing how spreads and forecasting uncertainty impact long-term outcomes.

- **Support renewable integration:** Examine how co-located BESS can mitigate solar curtailment and enhance ERCOT's system reliability by shifting excess renewable output into peak periods.

Taken together, these objectives provide a structured framework for developers and investors, ensuring that nodal differences, technical performance, and financial feasibility are jointly considered in decision-making.

2. State of the Art

2.1 ERCOT Market Operations

The Electric Reliability Council of Texas (ERCOT) operates independently from the Eastern and Western interconnections, making it a self-contained electricity market with over 17,000 pricing nodes. Prices are set through locational marginal pricing (LMP), which captures real-time supply-demand conditions and congestion at each settlement point. This nodal structure incentivizes geographically optimized development, as generators and increasingly BESS developers can site projects where volatility is greatest, to correct part of that volatility through a financially lucrative project.

Short-term trading in ERCOT is structured around two core markets. The Day-Ahead Market (DAM) establishes hourly schedules one day in advance, providing hedging value and early visibility into system conditions. The Real-Time Market (RTM), by contrast, settles every five minutes, reflecting the most immediate supply–demand imbalances. For BESS operators, the DAM offers predictable arbitrage opportunities, while the RTM provides exposure to extreme spreads that can reach hundreds of dollars per MWh in a single day. Long-term trading in ERCOT includes the Congestion Revenue Rights (CRR) Auction and bilateral trades, where financial energy contracts such as Power Purchase Agreements (PPAs) are negotiated.

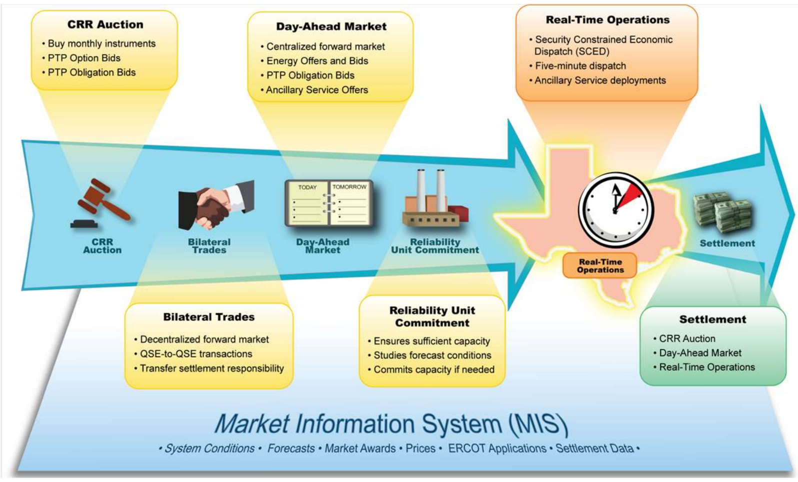


Figure 4. ERCOT market structure across timeframes, including DAM, RTM, and ancillary services [1]

These markets are complemented by the Ancillary Services Market, which ensures operational stability. Services include Regulation Up, Regulation Down, Responsive Reserve, Non-Spin Reserve, and the Contingency Reserve Service (ECRS), introduced in 2023. BESS participation has been particularly strong in these fast-response products. In the first half of 2023, ancillary services accounted for 87% of storage revenues, highlighting their role as an early anchor for the technology [3]. However, market data suggests this segment is nearing saturation, and long-term viability will depend more on energy arbitrage.

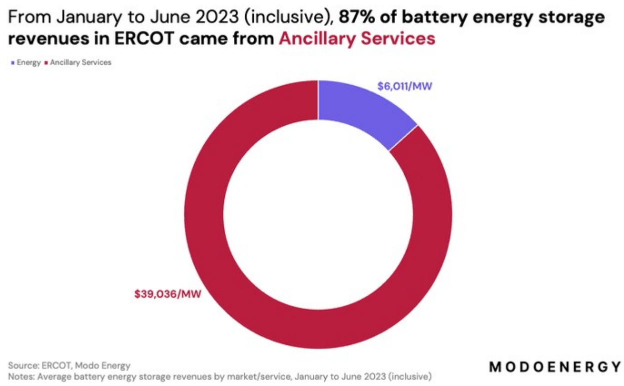


Figure 5. BESS revenue breakdown in ERCOT, January–June 2023, showing dominance of ancillary services [3]

Beyond short-term operations, ERCOT also supports longer-horizon mechanisms such as bilateral trading, Congestion Revenue Rights (CRR), and the Reliability Unit Commitment (RUC). While these play a role in overall system balance, the absence of a centralized capacity market distinguishes ERCOT from most other U.S. ISOs and places even greater weight on price signals.

Volatility has been reinforced by renewable integration. Wind and solar now account for more than 40% of ERCOT's generation mix, creating frequent curtailment and negative pricing events during oversupply, and sharp evening ramps as solar output fades. Extreme events, such as the 2021 Uri winter storm, underscored the risks of thermal outages and the value of dispatchable capacity; wholesale prices reached the $9,000/MWh cap for 77 consecutive hours during the crisis [4].

These dynamics make ERCOT one of the most favorable U.S. markets for BESS. Batteries can absorb energy during negative-priced hours, discharge into evening peaks, and provide rapid system reserves, turning volatility into revenue while enhancing grid resilience.

2.2 Utility-Scale Battery Energy Storage Technologies

BESS have emerged as a cornerstone of modern grid infrastructure, driven by rapid cost declines and performance improvements in electrochemical technologies. Global installations surpassed expectations in 2024, reaching 205 GWh, a 53% year-on-year increase, of which nearly 98% relied on lithium-ion chemistries [5]. In the United States, growth has been equally striking, exceeding 30% annually, with ERCOT representing one of the most dynamic markets thanks to its high share of variable renewables and reliance on price volatility to balance supply and demand.

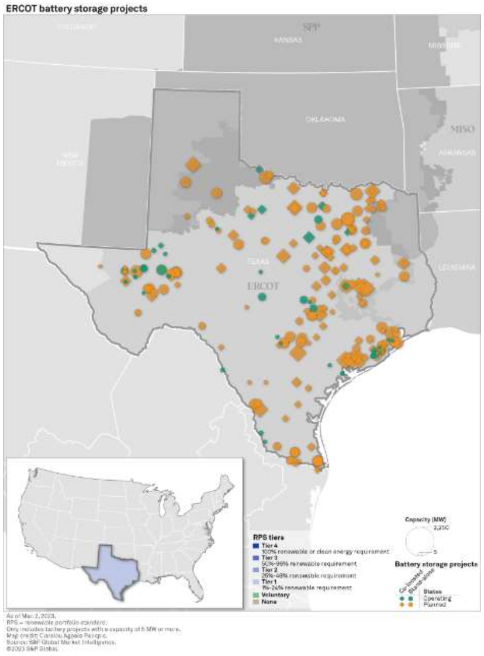


Figure 6. Standalone and co-located BESS facilities in the ERCOT market (S&P Global, 2024)

Operating principle and architecture

At their core, BESS operate by storing electricity in electrochemical form during low-price or low-demand periods and releasing it later when demand or system stress is high. This capability enables them to smooth renewable variability, provide fast-response ancillary services, and support grid reliability during extreme events. While multiple chemistries have been explored for utility-scale applications, including lead-acid, sodium-sulfur, and redox-flow systems, lithium-ion has emerged as the dominant technology due to its superior energy density, declining costs, and established manufacturing base.

Utility-scale BESS are built as integrated systems combining several subsystems. At the cell level, thousands of lithium-ion units are assembled into modules, racks, and finally containerized systems designed for outdoor operation. These are coupled with a Battery Management System (BMS), which continuously monitors temperature, voltage, and State of Charge (SoC) to ensure safe operation. The Power Conversion System (PCS) enables bidirectional flows of electricity by converting the battery's direct current (DC) to alternating current (AC), typically via an inverter and step-up transformer. To integrate the asset into grid operations, an Energy Management System (EMS) and SCADA platform optimize charging and discharging according to market signals and technical constraints.

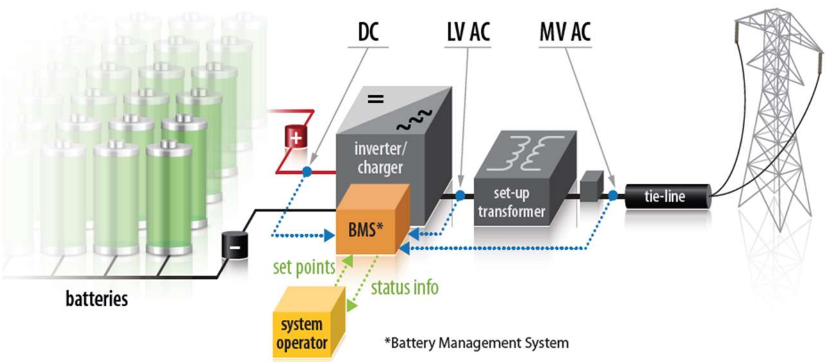


Figure 7. Key components of BESS interconnected at the transmission substation level (TESLA, 2025)

Beyond these core elements, several auxiliary subsystems are required for reliable utility-scale operation. Dedicated control rooms host SCADA servers and monitoring platforms, while metering cabinets ensure compliance with ERCOT's import/export requirements. High-Voltage

Customer (HVC) kiosks act as safety interfaces with the grid, isolating the system during maintenance or contingencies. Battery containers also house fire suppression systems and environmental controls, with HVAC units playing a particularly important role in hot climates such as West Texas, where ambient conditions can otherwise accelerate degradation and reduce battery lifetime.

Duration classes and applications of Lithium-Ion batteries

Within ERCOT, lithium-ion storage projects are generally categorized by their discharge duration, with distinct roles for each class. One-hour batteries remain focused on ancillary service provision, particularly frequency regulation, where rapid response is critical. Two-hour systems, the main focus of this study, are increasingly deployed for energy arbitrage, capturing spreads between midday low-price periods and evening peaks, though they also compete effectively in ancillary services. Four-hour systems are emerging as solutions for peak shaving and capacity firming, while eight-hour projects remain largely pre-commercial but are attracting interest as potential replacements for mid-merit gas generation. This spectrum of durations reflects not only technical maturity but also the evolving needs of ERCOT's energy-only market.

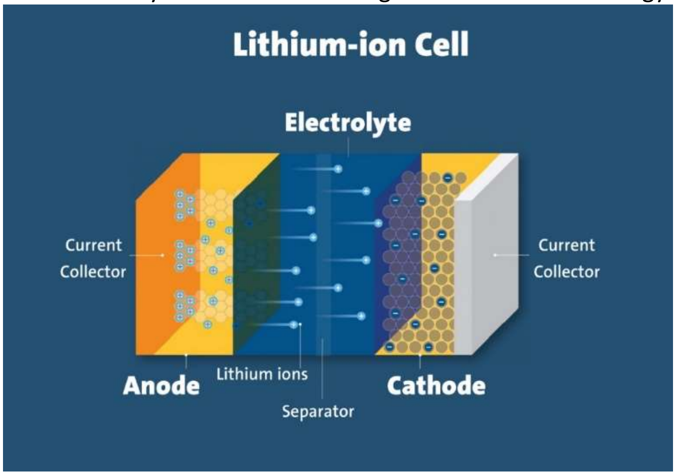


Figure 8. Lithium-ion cell composition [6]

Advantages of lithium-ion systems

Lithium-ion has become the dominant chemistry in utility-scale storage due to a combination of technical and economic factors. Its high energy density minimizes land use: for example, a 100 MW two-hour BESS may require roughly 5 acres, compared to more than 250 acres for an equivalent solar facility, underscoring the compactness and lower environmental footprint of storage. The modular architecture of containerized units also allows flexible scaling, from tens of megawatts in distribution-connected projects to several hundred megawatts at transmission-connected hubs.

From an operational perspective, lithium-ion BESS respond within milliseconds, making them well-suited for fast-frequency services and congestion management. Round-trip efficiencies between 85% and 93% ensure that most of the stored energy can be used and monetized, while lifetime expectations of 4,000 to 6,000 full equivalent cycles translate into calendar lifespans of 10-15 years under typical conditions. These attributes, coupled with cost declines of nearly 90% since 2010, have consolidated lithium-ion's role as the benchmark technology for grid-scale storage.

Limitations and challenges

Despite their advantages, lithium-ion batteries face several constraints. Performance degrades under thermal stress: high temperatures accelerate chemical ageing and risk thermal runaway, while very low temperatures increase internal resistance and raise the likelihood of lithium plating. Their duration is also limited, typically between one and four hours, which restricts suitability for long-duration applications such as seasonal shifting. Material supply chains for lithium, cobalt, and nickel present further risks, both in terms of cost volatility and ethical sourcing. Safety concerns remain as well, since most lithium-ion chemistries use flammable electrolytes. Incidents such as the 2019 Arizona facility fire highlight the importance of robust fire suppression and emergency protocols [12].

Degradation mechanisms and operational parameters

Understanding degradation is critical to assessing both technical and economic performance. Calendar ageing occurs even when the battery is idle, accelerated by high SoC and elevated temperatures, while cycle ageing is driven by repetitive charging and discharging at high Depth of Discharge (DoD) or high C-rates (charge rates). These processes gradually reduce usable capacity and efficiency, with annual fade rates typically between 1.8% and 2.5% [7].

Key operational levers include [7]:

- **State of Charge (SoC):** Operating between 20-80% mitigates accelerated ageing compared to consistently high SoC.
- **Depth of Discharge (DoD):** Shallower cycling extends lifetime; reducing DoD from 100% to 50% can nearly double the number of full cycle equivalents (FCEs).
- **Temperature:** Maintaining container environments around 20-30°C is essential, with HVAC systems consuming non-negligible energy in hot climates.
- **Round-trip efficiency (RTE):** High RTE improves arbitrage economics and Internal Rate of Return (IRR), though it declines gradually as internal resistance builds.
- **State of Health (SoH):** A measure of remaining capacity and efficiency relative to nominal values, with 70-75% commonly used as end-of-life thresholds.

Auxiliary consumption, primarily HVAC loads, further influences net system efficiency and OPEX, particularly in ERCOT's hot summers. Nevertheless, modern utility-scale systems achieve availabilities above 95%, with some approaching 99% thanks to predictive maintenance and advanced monitoring.

Table 1. Summary of key operational parameters in utility-scale BESS

Parameter	Optimal Range	Impact on Performance
State of Charge (SoC)	20–80% (≈50% mid-SoC)	Limits accelerated ageing, extends lifetime.
Depth of Discharge (DoD)	≤70% per cycle	Lower DoD improves longevity, higher DoD increases throughput but accelerates degradation.
Temperature	20–30 °C	Optimal thermal window; deviations cause resistance buildup, plating, or accelerated degradation.
Round-Trip Efficiency (RTE)	85–93%	Higher RTE improves economic returns and usable output.
State of Health (SoH)	≥70–75%	Below threshold signals end-of-life; typical fade 1.8–2.5% per year.
Auxiliary Consumption	Minimized via efficient HVAC	Excessive loads reduce net efficiency and raise OPEX.
Availability	>95% (up to 99% in modern systems)	Ensures revenue stability and investor confidence.

Together, these technical characteristics determine the lifetime energy throughput, Levelized Cost of Storage (LCOS), and ultimately the financial viability of storage projects in ERCOT. As shown in the following sections, degradation-aware dispatch and accurate techno-economic modeling are essential to align technical constraints with market opportunities.

2.3 Economics and Market Viability of BESS in ERCOT

Lithium-ion technology currently dominates the utility-scale storage sector, representing approximately 98% of global deployments. Its position has been secured by a favorable combination of high energy density, declining costs, and a well-established manufacturing base. According to the International Energy Agency (IEA), lithium-ion battery pack prices have fallen from nearly $1,100/kWh in 2010 to below $150/kWh in 2024, a reduction of over 85% [5]. Alternative chemistries such as sodium-ion, solid-state, flow batteries, and iron-air systems are emerging as competitors, offering potential improvements in safety, longevity, or long-duration capabilities. Nevertheless, lithium-ion remains the standard for BESS projects due to its proven performance and mature supply chain.

Ongoing technological innovation is expected to reinforce this dominance while gradually opening the door to complementary chemistries. Advances in grid-forming inverters, AI-assisted dispatch optimization, and long-duration energy storage systems (LDES) are likely to expand the operational value of storage. In particular, iron-air and liquid-metal batteries, capable of discharging for more than ten hours, could eventually provide alternatives to conventional thermal resources in ancillary service markets. For the near term, however, lithium-ion's versatility in short- and medium-duration applications ensures its continued market leadership.

The financial viability of BESS projects depends on a balance between capital costs, operational expenses, and the ability to access multiple revenue streams. NREL projections estimate capital expenditures for utility-scale storage will average around $750,000 per MW by 2027 under moderate cost assumptions [8]. Figure 6 illustrates cost trajectories across conservative, moderate, and advanced scenarios.

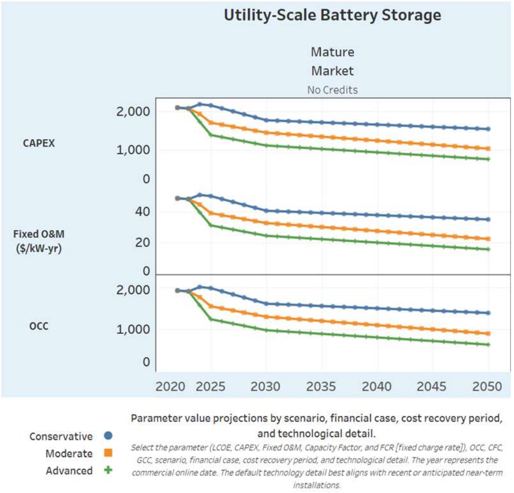


Figure 9. Utility-Scale Battery Storage costs projections based on 3 scenarios: Conservative, moderate, and advanced. (NREL, 2024) [8]

The ERCOT market structure provides an especially favorable environment for BESS development. Unlike other U.S. regions, ERCOT operates without a centralized capacity market, instead relying entirely on nodal energy pricing and ancillary services. This fully deregulated framework allows storage operators to monetize volatility directly, capturing spreads between the Day-Ahead and Real-Time markets while also providing ancillary services. The Inflation Reduction Act has further strengthened the investment case by introducing a 30% Investment Tax Credit (ITC) for standalone storage beginning in 2023, substantially improving bankability for BESS projects [9].

Developer interest is reflected in ERCOT's interconnection queue, which surpassed 90 GW of battery projects by early 2025. While only a fraction (less than 30%) of these projects are expected to reach operation, the scale of proposed capacity highlights growing confidence in storage economics. Many of the largest projects, developed by firms such as ENGIE, Iberdrola, and NextEra, are designed to operate BESS, without long-term Power Purchase Agreements, relying instead on flexible trading and nodal optimization. Table 2 summarizes the main categories of developers currently active in ERCOT's storage queue.

Table 2. Developers with BESS projects in ERCOT's interconnection queue by late 2024

Type of Developer	Companies	Sum of MW	Min Project size
Big	ENGIE, Iberdrola, NextEra, etc	> 500 MW	150 MW
Medium	Gransolar, PineGate, Abei	> 500 MW	< 150 MW
Small	Terra-Gen, Ignis Group, Redeux Energy	< 500 MW	10MW

Despite this momentum, BESS projects face risks that must be carefully managed. Historically, ancillary services have provided a large share of BESS revenues, particularly through Regulation Up, Regulation Down, and more recently the Enhanced Contingency Reserve Service (ECRS).

Since its launch in June 2023, ECRS has delivered some of the highest per-MW revenues for storage assets, with batteries comprising 20-30% of awarded capacity. However, Modo Energy data indicate that ancillary service markets are approaching saturation, with full capacity expected by late 2024. As competition increases, clearing prices are likely to decline, particularly for one-hour systems, raising concerns about long-term revenue cannibalization [3].

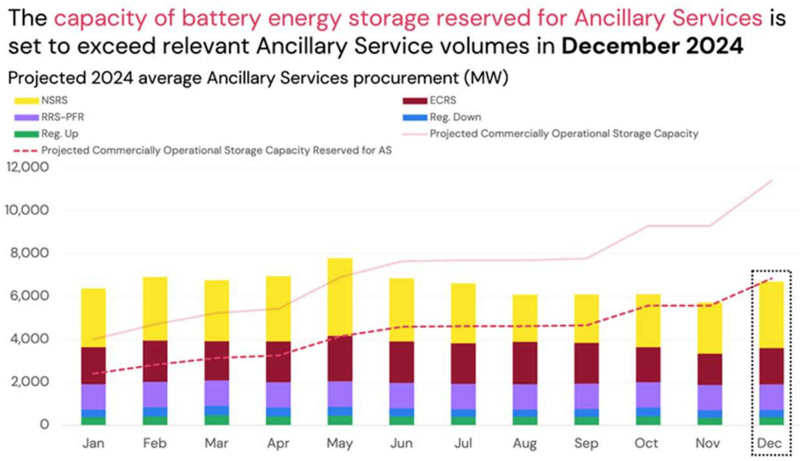


Figure 10. Projected saturation of ancillary service capacity in ERCOT by end of 2024 [3]

In this context, energy arbitrage emerges as the most sustainable revenue stream for two-hour systems, complemented by ancillary services when available. Yet real-time volatility also introduces uncertainty, especially at nodes with limited congestion relief. These dynamics highlight the importance of location-specific modeling, degradation-aware dispatch, and financial structuring to ensure that projects remain viable in ERCOT's evolving landscape.

2.4 Limitations of Current Practices in ERCOT

Despite ERCOT's rapid uptake of battery energy storage systems, current operational practices remain limited, constraining the ability of storage to fully capture value. One key shortcoming is the lack of nodal-level optimization. While ERCOT prices are settled across more than 17,000 nodes, many projects are sited and operated based on hub-level averages, neglecting significant locational variability. This results in suboptimal siting, missed arbitrage opportunities, and diminished economic returns.

Curtailment awareness is another underutilized strategy, particularly for co-located solar-plus-storage in West and South Texas, where midday negative prices frequently occur. Many systems fail to systematically exploit these charging windows, leaving potential revenues untapped.

From a technology perspective, alternative long-duration storage (e.g., flow batteries) offers promising advantages such as longer lifetimes and reduced degradation risks [11]. However, higher upfront costs, lower energy density, and greater mechanical complexity currently limit their competitiveness relative to lithium-ion solutions. However, according to several sources, flow batteries market growth will increase the next years, increasing lithium-ion's competitive landscape, thus developing storage technologies further, which although a limitation as of now, might be a source of opportunity to make projects more feasible in the future.

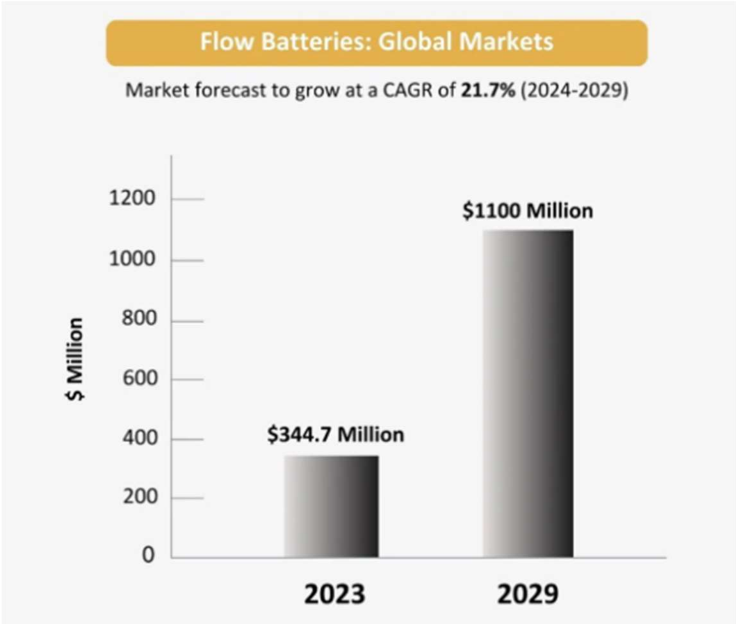


Figure 11. Global flow battery market growth outlook, 2024–2029 (BCC Research) [10]

Finally, most commercial BESS projects still rely on simple dispatch algorithms that ignore degradation dynamics. The absence of degradation-aware strategies leads to unnecessarily aggressive cycling, accelerating capacity fade and reducing system lifetimes. Addressing these limitations will require more granular nodal modeling, curtailment integration, and advanced control strategies to ensure long-term market and technical viability, all of which will be mentioned in chapter 3.

3. Model Development (Methodology)

This chapter describes the methodology used to develop a techno-economic model for evaluating utility-scale BESS within ERCOT. Building on the research objectives outlined earlier, the model simulates the daily operation of a 2-hour lithium-ion battery installation under realistic market conditions, leveraging Day-Ahead Market (DAM) price data across ERCOT's 17,000+ nodes from March 2021 to September 2024. The model integrates technical dispatch logic, battery degradation mechanisms, and financial assumptions, providing a decision-support tool for developers and investors, which in turn translated into reduced external studies' costs needed to analyze a specific node.

3.1 Data Architecture

The model is designed as a nodal-level techno-economic simulator that captures both operational and financial performance of BESS in different locations in ERCOT. At its core, the model evaluates DAM price spreads and calculates optimal charging and discharging schedules under realistic technical constraints, including State of Charge (SoC), Depth of Discharge (DoD), RTE, and auxiliary HVAC consumption or inner cooling systems consumption, if the battery architecture bought comprises of integrated inner cooling systems. These technical layers are linked to financial metrics such as CAPEX, OPEX, tax credits, and debt-equity structures, ensuring that results reflect both engineering feasibility and project bankability.

$$\begin{aligned}
&Button\ press\ \rightarrow Python\ activation\ through\ Excel\ Macro\ \rightarrow \\
&SQL\ Data\ extraction\ from\ available\ databases\ through\ python\ command\ \rightarrow \\
&Data\ load\ into\ existing\ model\ \rightarrow Dispatch\ calculation\ \rightarrow \\
&New\ Excel\ saved\ by\ the\ name\ '"Node"_BESS' \quad (1)
\end{aligned}$$

A robust data architecture was necessary to handle ERCOT's large dataset. DAM locational marginal price (LMP) data from March 2021–September 2024, spanning over 17,000 nodes and 3.9 million hourly values, was initially collected in CSV format from ERCOT's public archive [1]. Early testing employed a Python–Excel interface, where a script extracted nodal price histories into a centralized spreadsheet. This enabled preliminary dispatch simulations at the node level, but scalability was limited, as processing times grew rapidly with larger datasets.

To improve efficiency, a structured SQL database was implemented. LMP data were organized into yearly databases (e.g., LMP_2022, LMP_2023), with tables indexed by node, date, and hour. The Python code was adapted to query SQL directly, retrieving nodal prices in real time and feeding them into the Excel-based dispatch engine. A macro-enabled button in Excel allowed users to select a node and run simulations seamlessly, with results automatically saved as node-specific files.

Figures 21 and 22 illustrate the evolution of this pipeline: from CSV-based collection to SQL-driven databases, culminating in an automated Excel–Python–SQL integration that reduces runtime to approximately one minute per node.

DeliveryDate	HourEnding	SettlementPoint	SettlementPointPrice	2-Hour Point Prices DAM	MAX 2-Hour PP (RT-DAM)
01/03/2021	1:00	0	0	0	0
01/03/2021	2:00	0	0	0	0
01/03/2021	3:00	0	0	0	0
01/03/2021	4:00	0	0	0	3,2275
01/03/2021	5:00	0	0	0	20,47
01/03/2021	6:00	0	0	0	35,035
01/03/2021	7:00	0	0	0	40,095
01/03/2021	8:00	0	0	0	49,7275
01/03/2021	9:00	0	0	0	59,9625
01/03/2021	10:00	0	0	0	136,9275
01/03/2021	11:00	0	0	0	123,4975
01/03/2021	12:00	0	0	0	34,55
01/03/2021	13:00	0	0	0	32,015
01/03/2021	14:00	0	0	0	28,8575
01/03/2021	15:00	0	0	0	26,89
01/03/2021	16:00	0	0	0	27,68
01/03/2021	17:00	0	0	0	31,4325
01/03/2021	18:00	0	0	0	53,365
01/03/2021	19:00	0	0	0	69,0475
01/03/2021	20:00	0	0	0	75,1325
01/03/2021	21:00	0	0	0	68,3675
01/03/2021	22:00	0	0	0	49,305
01/03/2021	23:00	0	0	0	43,095
01/03/2021	24:00:00	0	0	0	38,4525
02/03/2021	1:00	0	0	0	36,0175
02/03/2021	2:00	0	0	0	34,24
02/03/2021	3:00	0	0	0	34,205
02/03/2021	4:00	0	0	0	35,445
02/03/2021	5:00	0	0	0	38,4975
02/03/2021	6:00	0	0	0	128,345
02/03/2021	7:00	0	0	0	141,2425
02/03/2021	8:00	0	0	0	54,345
02/03/2021	9:00	0	0	0	41,84
02/03/2021	10:00	0	0	0	38,815

Figure 12. Initial CSV-based data collection for ERCOT DAM nodal prices

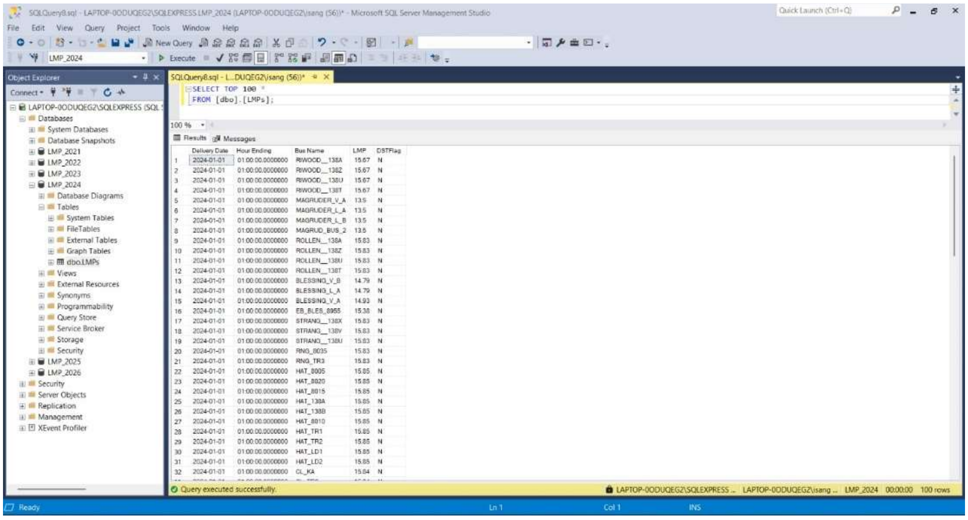


Figure 13. SQL database structure showing yearly LMP datasets (LMP_2022, LMP_2023, etc.)

This modular architecture ensures transparency and scalability. While the financial model itself operates within Excel for accessibility, the back-end SQL and Python integration enables high-resolution simulations across ERCOT's 17,000+ nodes. The combination balances computational efficiency with usability, supporting both academic analysis and practical application by developers and stakeholders involved.

3.2 Modeling Assumptions

To ensure scalable simulations of BESS performance under ERCOT market conditions, the model incorporates a structured set of technical, operational, and financial assumptions. These assumptions reflect both current industry standards for utility-scale lithium-ion systems and the unique dynamics of ERCOT's nodal market. Together, they establish the foundation for dispatch simulations and financial outputs.

The baseline system modeled is a 100 MW / 200 MWh lithium-ion BESS, a representative configuration for current ERCOT projects. This size can be adjusted flexibly within the model to reflect site-specific constraints or developer preferences, without altering the underlying degradation or operational logic. The system is assumed to operate at an initial RTE, measured at the inverter, of 93%, consistent with present technology performance, with an annual efficiency decline of 1% to capture aging effects [7]. Depth of Discharge (DoD) is set at 95% in the base case, reflecting aggressive cycling that maximizes short-term energy throughput, while alternative configurations (80%, 65%, 50%) are available to assess trade-offs between lifetime extension and revenue generation. Capacity fade is modeled at 1.95% per year under 95% DoD, in line with empirical studies investigated.

Temperature conditions are held constant at 25°C, representing optimal thermal management for lithium-ion installations. While real-world auxiliary consumptions fluctuate seasonally (more consumption in summer and less in winter), HVAC/inner cooling and balance-of-plant consumption are conservatively modeled as a flat 6% of annual potential revenues. This simplification captures the steady cost burden of thermal control, SCADA, and operational support. SoC is implicitly balanced: the system is modeled to charge and discharge symmetrically, maintaining an average SoC of roughly 50%, consistent with long-term stability strategies.

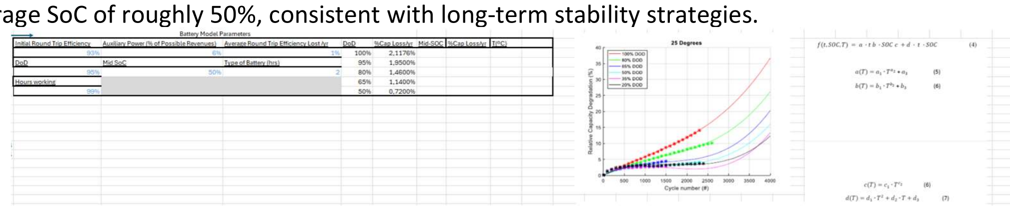


Figure 14. Input sheet in Excel showing core technical parameters and degradation assumptions implemented in the model

Battery lifetime is linked to cycling assumptions. Under a 1.5 cycles/day regime, the system operates over a 15-year horizon, while reducing cycling to 1 cycle/day extends the modeled life to 20 years. Seasonal patterns in ERCOT price data are embedded into the dispatch logic. During summer months (May–September), when prices typically peak once daily in the late evening, the model dispatches 1 cycle per day. In winter months (January–April, November–December), when two price peaks are observed, 2 cycles/day are simulated. Charging and discharging hours are dynamically assigned based on daily DAM price profiles, ensuring alignment with observed seasonal behavior.

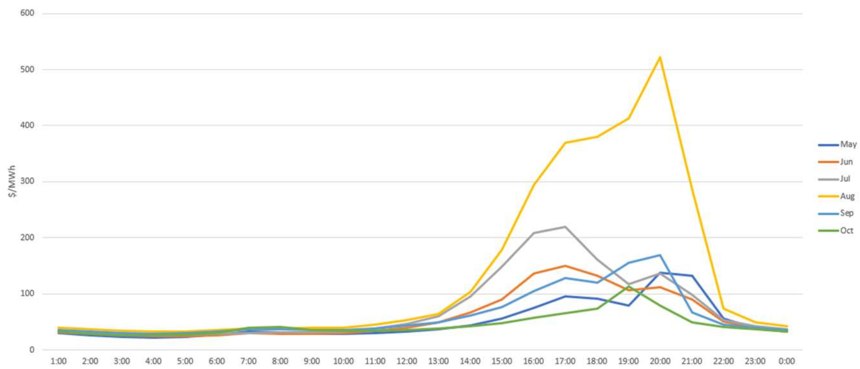


Figure 15. Average hourly DAM prices at a representative ERCOT node during summer (single daily peak)

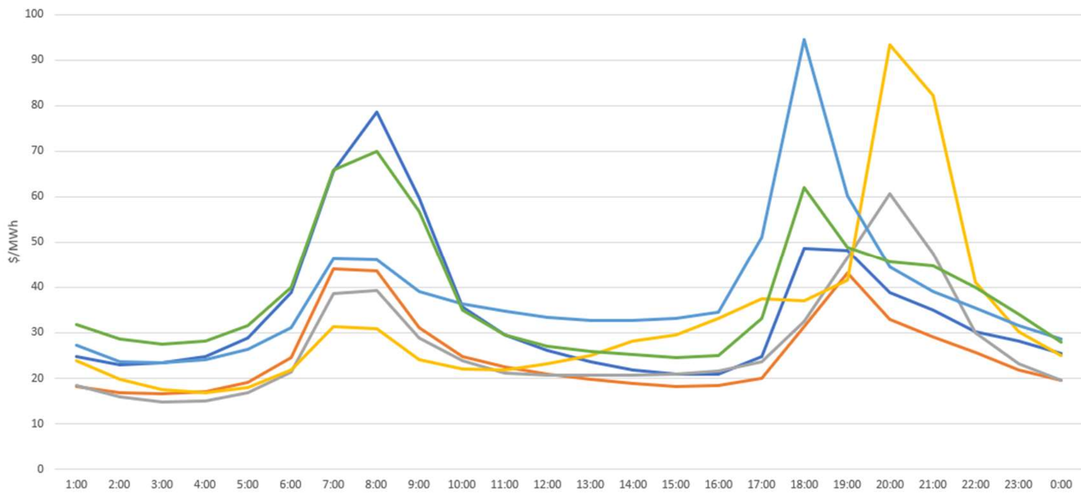


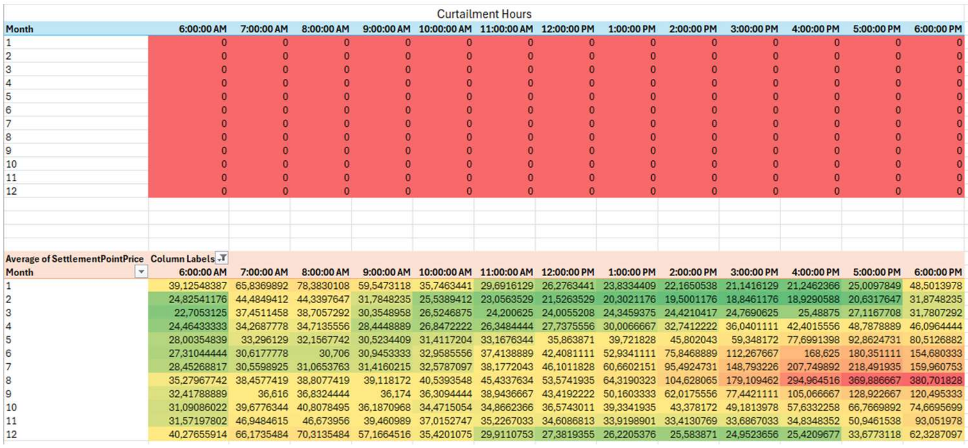
Figure 16. Average hourly DAM prices during winter months, showing two daily peaks

In addition to DAM-only strategies, the model includes an optional hybrid DAM–RT configuration. In this case, charging occurs in DAM's lowest-price hours, while discharging is assigned to the highest-price intervals in RTM for the same day [13]. Although this assumes perfect foresight and is therefore not realistic in practice, it functions as an upper-bound benchmark of the potential gains achievable with predictive algorithms or AI-based dispatch, where future work studies could be addressed.

MAX 2-Hour PP (RT-DAM)
19,76
2,16
2,25
4,25
6,75
20,47
35,035
48,55
52,97
59,9625
136,9275
123,4975
49,76
43,27
36
35,8
37,27
43,24
64,91

Figure 17. Model interface showing the DAM–RT hybrid dispatch column, used for sensitivity testing

To assess solar co-location opportunities, the model integrates a simplified curtailment model. Using ERCOT's historical curtailment hour counts and hourly DAM prices, the model estimates the "economic loss" of curtailed solar generation, known as solar hours where the DAM price is below zero, by summing curtailed MWh with the average nodal price at the relevant hour and month. This quantifies the baseline value lost in standalone solar projects. A co-located BESS, by storing this otherwise curtailed energy and shifting it to evening peaks, could recover additional revenues beyond this conservative baseline.



Curtailment Hours

Month	6:00:00 AM	7:00:00 AM	8:00:00 AM	9:00:00 AM	10:00:00 AM	11:00:00 AM	12:00:00 PM	1:00:00 PM	2:00:00 PM	3:00:00 PM	4:00:00 PM	5:00:00 PM	6:00:00 PM
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0

Average of SettlementPointPrice	Column Labels												
Month	6:00:00 AM	7:00:00 AM	8:00:00 AM	9:00:00 AM	10:00:00 AM	11:00:00 AM	12:00:00 PM	1:00:00 PM	2:00:00 PM	3:00:00 PM	4:00:00 PM	5:00:00 PM	6:00:00 PM
1	39,12548387	65,8369892	78,3830108	59,5473118	35,7463441	29,6916129	26,2763441	23,8334409	22,1650538	21,1416129	21,2462366	25,0097849	48,5013978
2	24,82541176	44,4849412	44,3397647	31,7848235	25,5389412	23,0563529	21,5263529	20,3021176	19,5001176	18,8461176	18,9290588	20,6317647	31,8748235
3	22,7053125	37,4511458	38,7057292	30,3548958	26,5246875	24,200625	24,0055208	24,3459375	24,4210417	24,7690625	25,48875	27,1167708	31,7807292
4	24,46433333	34,2687778	34,7135556	28,4448889	26,8472222	26,3484444	27,7375556	30,0066667	32,7412222	36,0401111	42,4015556	48,7878889	46,0964444
5	28,00354839	33,296129	32,1567742	30,5234409	31,4117204	33,1676344	35,863871	39,721828	45,802043	59,348172	77,6991398	92,8624731	80,5126882
6	27,31044444	30,6177778	30,706	30,9453333	32,9585556	37,4138889	42,4081111	52,9341111	75,8468889	112,267667	168,625	180,351111	154,680333
7	28,45268817	30,5598925	31,0653763	31,4160215	32,5787097	38,1772043	46,1011828	60,6602151	95,4924731	148,793226	207,749892	218,491935	159,960753
8	35,27967742	38,4577419	38,8077419	39,118172	40,5393548	45,4337634	53,5741935	64,3190323	104,628065	179,109462	294,964516	369,886667	380,701828
9	32,41788889	36,616	36,8324444	36,174	36,3094444	38,9436667	43,4192222	50,1603333	62,0175556	77,4421111	105,066667	128,922667	120,495333
10	31,09086022	39,6776344	40,8078495	36,1870968	34,4715054	34,8662366	36,5743011	39,3341935	43,378172	49,1813978	57,6332258	66,7669892	74,6695699
11	31,57197802	46,9484615	46,673956	39,460989	37,0152747	35,2267033	34,6086813	33,9198901	33,4130769	33,6867033	34,8348352	50,9461538	93,051978
12	40,27655914	66,1735484	70,3135484	57,1664516	35,4201075	29,9110753	27,3819355	26,2205376	25,583871	24,9523656	25,4209677	33,6773118	62,3287097

Figure 18. Curtailment heatmap combining curtailed hours with average nodal DAM prices by month and hour

For benchmarking purposes, the curtailment analysis is paired with a standard hourly generation profile of a 100 MW solar plant in ERCOT's North Hub, reflecting the region's significant development pipeline and frequent exposure to midday congestion.

NORMALIZED /100MW

	Month	1:00:00	2:00:00	3:00:00	4:00:00	5:00:00	6:00:00	7:00:00	8:00:00	9:00:00	10:00:00	11:00:00	12:00:00
31	January	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	-0,18	19,07	46,21	55,60	59,36	62,39
28	February	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	2,63	30,18	49,49	58,96	60,34	59,85
31	March	-0,24	-0,24	-0,24	-0,24	-0,24	-0,08	16,24	41,34	58,47	67,27	72,34	77,40
30	April	-0,25	-0,25	-0,25	-0,25	-0,25	4,72	27,78	61,22	76,24	80,66	88,16	86,03
31	May	-0,24	-0,24	-0,24	-0,24	-0,24	14,64	38,65	62,74	78,85	79,66	83,67	90,73
30	June	-0,25	-0,25	-0,25	-0,25	-0,25	20,11	47,32	70,78	82,64	90,90	86,87	90,86
31	July	-0,24	-0,24	-0,24	-0,24	-0,24	15,96	53,82	85,91	92,67	93,31	97,05	96,79
31	August	-0,24	-0,24	-0,24	-0,24	-0,24	6,86	40,55	77,15	91,09	93,46	93,01	90,81
30	September	-0,25	-0,25	-0,25	-0,25	-0,25	1,88	31,46	66,94	77,43	82,64	87,24	83,93
31	October	-0,24	-0,24	-0,24	-0,24	-0,24	-0,20	20,39	53,55	71,29	74,61	76,73	77,13
30	November	-0,25	-0,25	-0,25	-0,25	-0,25	-0,25	8,07	39,74	57,72	59,54	61,22	62,24
31	December	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	0,51	19,80	41,50	51,09	50,54	53,72

	Month	13:00:00	14:00:00	15:00:00	16:00:00	17:00:00	18:00:00	19:00:00	20:00:00	21:00:00	22:00:00	23:00:00	0:00:00	ENERGY PRODUCED /100MW/Month (MWh)
31	January	61,74	60,67	58,71	30,72	3,38	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	457,85
28	February	61,50	65,13	63,71	42,31	13,03	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	507,12
31	March	75,74	73,49	72,46	59,01	27,12	0,87	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	641,75
30	April	88,92	87,50	76,00	66,68	32,83	3,82	-0,25	-0,25	-0,25	-0,25	-0,25	-0,25	780,55
31	May	87,85	92,63	88,54	74,85	45,75	11,55	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	850,12
30	June	89,12	87,71	75,85	70,97	52,20	18,85	-0,25	-0,25	-0,25	-0,25	-0,25	-0,25	884,18
31	July	85,63	82,31	85,61	77,68	55,62	19,13	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	941,49
31	August	89,75	90,14	87,89	75,90	43,02	8,60	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	888,24
30	September	85,03	78,96	75,85	54,92	20,44	0,12	-0,25	-0,25	-0,25	-0,25	-0,25	-0,25	746,85
31	October	74,38	72,69	68,48	37,19	5,32	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	631,76
30	November	64,22	66,72	54,27	21,40	-0,25	-0,25	-0,25	-0,25	-0,25	-0,25	-0,25	-0,25	495,14
31	December	57,40	55,64	47,71	20,67	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	-0,24	398,60

Figure 19. Representative 100 MW solar generation profile in ERCOT's North Hub

All modeling assumptions are summarized in the following concise table, providing clarity and reproducibility for subsequent simulations.

Table 3. Executive summary of technical, operational, and financial modeling assumptions

Category	Parameter	Value / Assumption
System size	Battery capacity	User-defined; 100 MW / 200 MWh base case
Lifetime	Project horizon	15 years (1.5 cycles/day) or 20 years (1 cycle/day)
Efficiency	Initial RTE	93%, declining 1% annually
Losses	HVAC & auxiliaries	6% of annual revenues
Degradation	DoD	95% (options: 80%, 65%, 50%)
	Capacity fade	1.95%/year (at 95% DoD)
	SoH threshold	70%
Dispatch	Seasonal cycles	1/day summer, 1.5/day winter
	Rule	Charge at 2 cheapest hours, discharge at 2 peak hours
	Hybrid mode	DAM charging + RT discharging (upper-bound)
Financials	CAPEX & OPEX	Based on NREL cost curves; OPEX = 3.5% CAPEX
	Incentives	30% ITC; MACRS-style depreciation
Co-location	Curtailment value	Lost MWh × average nodal DAM price
	Solar benchmark	100 MW North Hub profile

3.3 Algorithmic Logic

The central component of the techno-economic model is the dispatch algorithm, designed to emulate real-world battery behavior under ERCOT's nodal price dynamics. The logic is built to balance computational efficiency with technical realism, capturing how a two-hour BESS would perform when exposed to historical locational marginal pricing (LMPs). By applying deterministic rules for charging and discharging while embedding seasonal cycles and degradation effects, the algorithm ensures transparent and repeatable outputs.

The core operation begins with hourly DAM price data, organized as 24 rows per day from March 2021 through September 2024. For each day, the algorithm identifies two consecutive hours with the lowest LMPs, designating them as the charging window. Similarly, the two consecutive hours with the highest LMPs are chosen as the discharging window. This rule-based approach reflects a value-maximizing arbitrage strategy, ensuring symmetry and avoiding simultaneous charge-discharge actions. Each cycle maintains an average SoC of 50% approximately, consistent with the assumptions defined in Section 3.2.

	January	February	March	April	May	June	July	August	Septembe	October	November	December
	1	2	3	4	5	6	7	8	9	10	11	12
MIN(2)	36,58075269	26,24223529	26,9028226	30,99575	39,19346774	45,7315	47,07612903	56,25379	50,43033	52,53747	43,17923077	38,51871
MAX(2)	163,0677419	114,5492941	135,770403	183,3878	318,5876613	351,01125	362,5026613	817,0515	282,8966	226,2522	172,8038462	174,4757
2-HOUR DIFF	126,4869892	88,30705882	108,867581	152,3921	279,3941935	305,27975	315,4265323	760,7977	232,4663	173,7147	129,6246154	135,957

	January	February	March	April	May	June	July	August	Septembe	October	November	December
	1	2	3	4	5	6	7	8	9	10	11	12
MIN	18,29037634	13,12111765	13,4514113	15,49788	19,59673387	22,86575	23,53806452	28,1269	25,21517	26,26874	21,58961538	19,25935
MAX	81,53387097	57,27464706	67,8852016	91,69392	159,2938306	175,505625	181,2513306	408,5257	141,4483	113,1261	86,40192308	87,23785
1-HOUR DIFF	63,24349462	44,15352941	54,4337903	76,19604	139,6970968	152,639875	157,7132661	380,3988	116,2331	86,85737	64,81230769	67,97849

Figure 20. Average daily identification of cheapest (charge) and most expensive (discharge) hours per month

To operationalize this process, the simulation proceeds as follows:

For each day, scan 24 hourly DAM prices

Identify two lowest consecutive hours → charge cycle

Identify two highest consecutive hours → discharge cycle

If in a winter month (January–April, November–December), repeat steps 2–3 for a second daily cycle (1.5 cycles/day)

Calculate daily energy arbitrage revenue from price spreads

Aggregate daily results into monthly and annual averages

Apply annual degradation adjustments to reflect reduced capacity and round-trip efficiency

Figure 21. Simplified pseudocode of the daily BESS dispatch algorithm

After each node's daily cycles are simulated, the algorithm aggregates performance indicators, or KPIs, into a dedicated Excel output file. These outputs include monthly averages, annual revenues, energy throughput, degradation-adjusted KPIs, and hub-level comparisons. The process is triggered via an Excel macro button, which first activates a Python script to retrieve nodal LMPs directly from the SQL database. Once prices are loaded, the VBA logic executes the cycle assignment, calculates revenues, and exports results. Output files are automatically named according to the node under analysis (e.g., HoustonWestNode_BESS.xlsx), streamlining node-by-node evaluations.

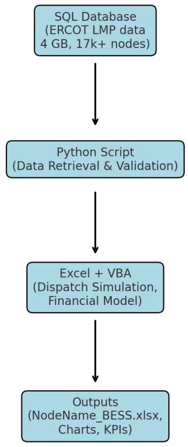


Figure 22. Workflow for aggregating dispatch results and exporting nodal KPIs

Seasonality is explicitly embedded into the algorithm. Empirical ERCOT price patterns show that summer months (May–September) are characterized by single evening peaks, whereas winter months typically exhibit dual peaks, midday and evening. This seasonal adjustment is critical, as it directly influences the profitability and long-term feasibility of storage projects, which will be discussed in the sensitivity analysis.

The model further incorporates degradation logic, applied annually to revenues and capacity factors. RTE declines by 1% per year, while usable capacity decreases according to DoD assumptions (1.95% per year at 95% DoD) [7]. By applying these adjustments externally, the algorithm maintains a modular structure in which dispatch behavior and performance decay remain distinct, facilitating sensitivity analyses.

In addition, Co-location opportunities are evaluated through a parallel curtailment simulation module. Using historical data on curtailment frequency and nodal DAM prices, the model estimates the baseline economic value of curtailed solar generation. These values are not used as charging inputs for BESS but rather as an indication of the opportunity cost solar projects incur during oversupply or congestion periods. By comparing this with BESS arbitrage revenues, developers can assess whether co-located projects are financially attractive relative to standalone installations.

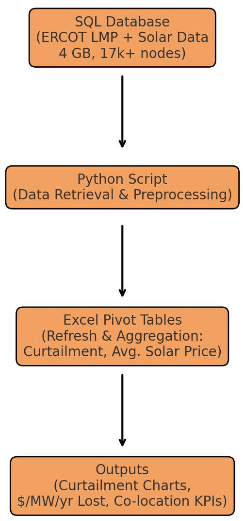


Figure 23. Workflow diagram of curtailment estimation module, operating independently from BESS dispatch

In summary, the algorithmic logic combines simplicity and scalability with enough technical depth to reflect ERCOT's complex price dynamics. By anchoring simulations in deterministic charge-discharge windows, integrating seasonal cycle patterns, and layering degradation and financial post-processing, the model achieves a balance between accuracy, transparency, and usability. These attributes make it suitable both for granular nodal analysis and for broader hub-level benchmarking.

3.4 Tech Stack

The developed techno-economic model is built on an integrated architecture combining Excel/VBA, Python, and SQL, with each environment performing a distinct yet complementary role. This configuration was reached through trial and error, balancing runtime efficiency, simplicity and accessibility for non-technical users. While Python and SQL handle large-scale data processing and retrieval, Excel and VBA remain the central interface where dispatch simulations, parameter adjustments, and financial evaluations are conducted. This hybrid structure ensures computational robustness without sacrificing usability for developers and decision-makers.

Excel and VBA - Core Model Environment

Excel serves as the primary user interface, hosting parameter input sheets, results dashboards, and graphical summaries of key performance indicators. The dispatch simulation engine is implemented in VBA, chosen for its transparency and direct link to financial outputs. Annual revenues, derived from arbitrage strategies, are calculated by VBA macros and automatically fed into embedded financial formulas to generate metrics such as internal rate of return (IRR), net present value (NPV), and payback period. The interface design prioritizes simplicity: the user selects a node, presses a single "Run Model" button, and results populate dynamically, including updated tables and figures.

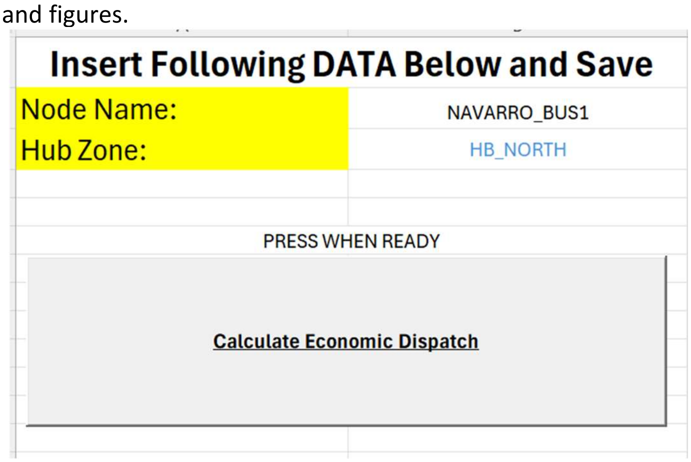


Figure 24. Excel interface with node selector and macro button, enabling full automation of dispatch simulation

Python - Data Retrieval and Validation Layer

Python operates as an intermediary between SQL and Excel. Using packages such as pandas, pyodbc, and openpyxl, it queries the SQL database, retrieves the full hourly DAM price profile for the selected node, and transfers it directly into the Excel model. To safeguard data integrity, validation routines verify that the node exists and that the expected number of hourly records (8,760 per year) is present. If either condition fails, the process halts before dispatch begins. This modular design ensures separation of responsibilities: Python focuses exclusively on reliable data transfer and updating the SQL database if need be, leaving simulation logic to VBA and storage management to SQL.

```python
# Load the existing macro-enabled workbook
try:
    book = load_workbook(input_excel_path, keep_links=True, keep_vba=True)

    # Copy data from "Input Sheet" to "SummarySheet"
    input_sheet = book['Input Sheet']
    summary_sheet = book['SummarySheet']
    summary_sheet['B1'] = input_sheet['B2'].value
    summary_sheet['B2'] = input_sheet['B3'].value

    # Remove the "Input Sheet"
    del book['Input Sheet']

    # Remove the existing sheet if it exists
    if 'FilteredData' in book.sheetnames:
        del book['FilteredData']

    # Load the filtered data from the temporary file
    temp_book = load_workbook(temp_excel_path, data_only=True)
    temp_sheet = temp_book['FilteredData']

    # Create a new sheet in the existing workbook for the filtered data
    target_sheet = book.create_sheet('FilteredData')

    # Copy the data from the temporary sheet to the new sheet in the existing workbook
    for row in temp_sheet.iter_rows(values_only=True):
        target_sheet.append(row)

    # Define the path for the new macro-enabled workbook
    new_excel_path = os.path.join(os.path.dirname(input_excel_path), f"{name_to_filter}.xlsm")

    # Save the updated workbook as a new macro-enabled workbook
    book.save(new_excel_path)
    print(f"Filtered data written to the new Excel file at {new_excel_path}")
```

Figure 25. Battery Valuation Python Script Extract

SQL - Large-Scale Data Management

The SQL Server database hosts more than 16GB of ERCOT LMP data, encompassing over 17,000 nodes across 3.5 years approximately. Data is structured into annual tables (e.g., LMP_2022, LMP_2023) with indexing by node, date, and hour, enabling rapid retrieval of node-specific time series. Before SQL integration, node-level runs required 5-10 minutes via CSV processing in Python, often saturating system RAM. SQL reduced retrieval times to <1 minute per node while lowering memory overhead, representing close to a 90% decrease in runtime. This efficiency gain enabled systematic benchmarking across ERCOT, which would have been computationally prohibitive with a CSV-based approach.

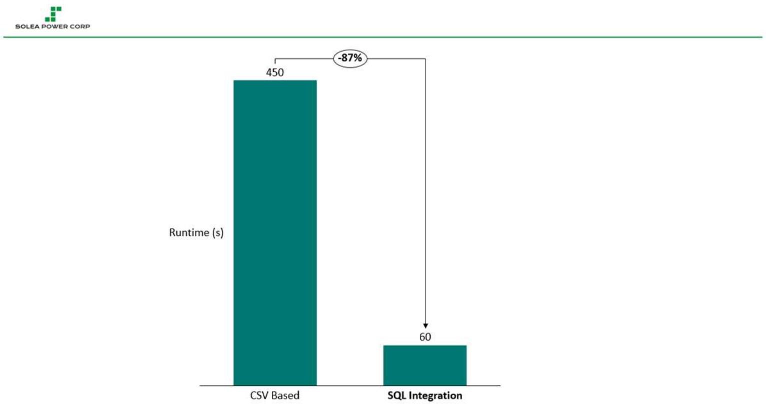


Figure 26. Comparison of average runtime before (CSV pipeline) and after SQL integration, showing around 90% efficiency gain

Scalability, Reproducibility, and Adaptability

The modular architecture was deliberately designed for scalability. Adding a new year of price data requires only importing it into SQL under a new table and updating a single line in the Python script, with no changes to VBA dispatch logic. The same model could be adapted to Real-Time Market (RTM) data or to incorporate machine-learning-assisted dispatch optimization. Reproducibility is also central: any analyst can operate the model by opening the master Excel file, selecting a node, and pressing a single button. Output files follow a consistent naming convention, ensuring traceability and comparability across nodes and hubs.

```
' Get the last row of the data
lastRow = ws.Cells(ws.Rows.Count, "A").End(xlUp).Row

' Loop through each column from J to U in row 11
For j = 10 To 21 ' Columns J to U are 10 to 21
    monthToFind = ws.Cells(12, j).Value

    ' Initialize the array to store minimum values
    ReDim maxValues(1 To Application.WorksheetFunction.RoundUp((lastRow / 24), 0))

    maxIndex = 1
    sumMaxValues = 0
    countMaxValues = 0

    ' Loop through the rows to find the maximum value for every 24 rows in the specified month
    For i = 3 To lastRow Step 24
        If ws.Cells(i, 6).Value = monthToFind Then
            maxValue = Application.WorksheetFunction.Max(ws.Range(ws.Cells(i, 4), ws.Cells(i + 23, 4)))
            maxValues(maxIndex) = maxValue
            maxIndex = maxIndex + 1
        End If
    Next i

    ' Calculate the average of the maximum values
    For i = 1 To maxIndex - 1
        sumMaxValues = sumMaxValues + maxValues(i)
        countMaxValues = countMaxValues + 1
    Next i

    If countMaxValues > 0 Then
        avgMaxValue = sumMaxValues / countMaxValues
        ws.Cells(14, j).Value = avgMaxValue
    Else
        ws.Cells(14, j).Value = "N/A"
    End If
Next j

For j = 10 To 21 ' Columns J to U are 10 to 21
    monthToFind = ws.Cells(12, j).Value

    ' Initialize the array to store minimum values
    ReDim minValues(1 To Application.WorksheetFunction.RoundUp((lastRow / 24), 0))

    minIndex = 1
    sumMinValues = 0
    countMinValues = 0
```

Figure 27. Extract of VBA automation code showing dispatch loop integration with SQL–Python pipeline

3.5 Financial Modeling

The financial model developed in this study translates the technical and market performance outputs of the dispatch model into an investment-grade cash flow projection. It goes beyond simple revenue estimation, integrating capital expenditure (CAPEX), operating expenditure (OPEX), tax incentives, depreciation, financing terms, and degradation into a unified analytical environment. The model is structured as a project finance special purpose vehicle (SPV), reflecting standard practice in Texas where each large-scale renewable or storage project is developed under a dedicated limited liability company (LLC). This ensures the analysis aligns with real-world financing conditions, where lenders evaluate projects on a stand-alone basis.

The objective of this layer is to determine the financial viability of 2-hour lithium-ion BESS deployment under different ERCOT locational conditions. Both unlevered project IRR (100% equity) and levered shareholder IRR (with debt service obligations) are calculated, providing insight for different investor perspectives. The model also incorporates the 30% standalone Investment Tax Credit (ITC) and accelerated MACRS five-year depreciation [15], both of which are critical to improving early cash flows and reducing payback times.

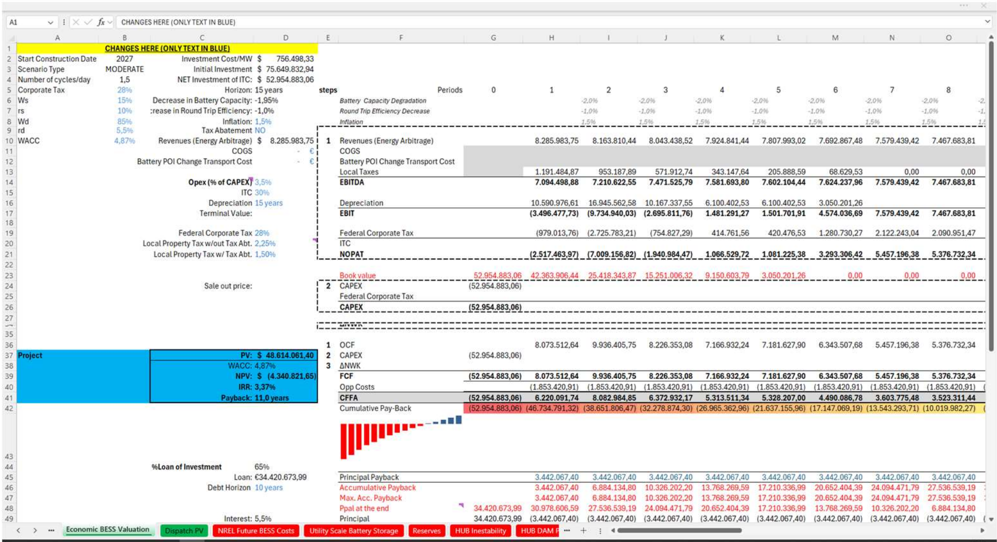


Figure 28. Extract of financial model showing CAPEX/OPEX inputs and IRR outputs

System Costs and OPEX

The base case assumes a 100 MW / 200 MWh BESS. CAPEX is drawn from NREL's Annual Technology Baseline, under three scenarios: Conservative, Moderate, and Optimistic, with Moderate as the default. To reflect market conditions, costs were adjusted from 2026 onwards to account for tariffs on Chinese imports of lithium-ion batteries announced in May 2024. The CAPEX breakdown highlights that battery modules remain the largest cost driver, though electrical BOS, EPC labor, and soft costs are also material.

OPEX is modeled at 3.5% of CAPEX annually, divided into 2.5% maintenance and 1% insurance. Augmentation is not pre-scheduled; instead, the system is run until capacity fade approaches end-of-life, consistent with BESS storage practice. This approach prioritizes early-year equity returns by avoiding cash outflows on mid-life reinvestments.

Future Costs - Storage Futures Study Utilty-Scale BESS

Results from the NREL Utility-Scale BESS model (current costs) with projections from NREL ATB 2020 Utility-Scale BESS Projections + BNEF battery cost projections
2019 System Costs in 2019 USD. Costs are presented in both $/kW and $/kWh.

	Future 60-MW BESS Costs ($/kW) - MID					Future 60-MW BESS Costs ($/kWh) - MID					
	2-hour	4-hour	6-hour	8-hour	10-hour	2-hour	4-hour	6-hour	8-hour	10-hour	
2018											
2019	902	1.554	2.206	2.858	3.509	451	389	368	357	351	-
2020	866	1.464	2.062	2.660	3.258	433	366	344	333	326	-
2021	829	1.373	1.918	2.462	3.007	414	343	320	308	301	-
2022	792	1.283	1.773	2.264	2.755	396	321	296	283	275	-
2023	755	1.192	1.629	2.066	2.503	377	298	272	258	250	-
2024	718	1.101	1.485	1.868	2.252	359	275	247	234	225	-
2025	681	1.011	1.340	1.670	2.000	340	253	223	209	200	-
2026	666	973	1.280	1.586	1.893	333	243	213	198	189	-
2027	649	935	1.221	1.507	1.793	325	234	204	188	179	-
2028	630	898	1.165	1.433	1.700	315	224	194	179	170	-
2029	610	860	1.111	1.361	1.612	305	215	185	170	161	-
2030	587	823	1.058	1.294	1.529	294	206	176	162	153	-
2031	585	812	1.040	1.267	1.495	292	203	173	158	149	-
2032	586	802	1.018	1.234	1.449	293	200	170	154	145	-
2033	586	792	998	1.203	1.409	293	198	166	150	141	-
2034	584	781	978	1.176	1.373	292	195	163	147	137	-
2035	582	771	961	1.150	1.339	291	193	160	144	134	-
2036	578	761	944	1.126	1.309	289	190	157	141	131	-
2037	574	751	927	1.104	1.280	287	188	155	138	128	-
2038	569	740	911	1.083	1.254	285	185	152	135	125	-
2039	564	730	896	1.062	1.229	282	182	149	133	123	-
2040	558	720	881	1.043	1.205	279	180	147	130	120	-
2041	552	709	867	1.024	1.182	276	177	144	128	118	-
2042	546	699	853	1.006	1.159	273	175	142	126	116	-
2043	539	689	839	988	1.138	270	172	140	124	114	-
2044	532	679	825	971	1.117	266	170	137	121	112	-
2045	525	668	811	955	1.098	263	167	135	119	110	-
2046	518	658	798	939	1.079	259	165	133	117	108	-
2047	510	648	785	923	1.060	255	162	131	115	106	-
2048	502	637	772	907	1.042	251	159	129	113	104	-
2049	495	627	760	892	1.025	247	157	127	112	103	-
2050	486	617	747	878	1.008	243	154	125	110	101	-

	Future 60-MW BESS Costs ($/kW) - LOW					Future 60-MW BESS Costs ($/kWh) - LOW					
	2-hour	4-hour	6-hour	8-hour	10-hour	2-hour	4-hour	6-hour	8-hour	10-hour	
2018											
2019	902	1.554	2.206	2.858	3.509	451	389	368	357	351	-
2020	703	1.210	1.718	2.226	2.733	351	303	286	278	273	-
2021	653	1.125	1.597	2.069	2.541	327	281	266	259	254	-
2022	604	1.040	1.476	1.912	2.349	302	260	246	239	235	-
2023	554	955	1.355	1.756	2.156	277	239	226	219	216	-
2024	505	870	1.234	1.599	1.964	252	217	206	200	196	-
2025	455	784	1.113	1.442	1.771	228	196	186	180	177	-
2026	431	742	1.053	1.364	1.675	215	185	175	170	168	-
2027	406	699	992	1.286	1.579	203	175	165	161	158	-
2028	381	656	932	1.207	1.482	191	164	155	151	148	-
2029	356	614	871	1.129	1.386	178	153	145	141	139	-
2030	332	571	811	1.050	1.290	166	143	135	131	129	-
2031	325	560	795	1.030	1.264	163	140	132	129	126	-
2032	319	549	779	1.009	1.239	159	137	130	126	124	-
2033	312	538	763	989	1.214	156	134	127	124	121	-
2034	306	526	747	968	1.189	153	132	125	121	119	-
2035	299	515	731	947	1.164	150	129	122	118	116	-
2036	293	504	715	927	1.138	146	126	119	116	114	-
2037	286	493	700	906	1.113	143	123	117	113	111	-
2038	280	482	684	886	1.088	140	120	114	111	109	-
2039	273	471	668	865	1.063	137	118	111	108	106	-
2040	267	459	652	845	1.037	133	115	109	106	104	-
2041	260	448	636	824	1.012	130	112	106	103	101	-
2042	254	437	620	804	987	127	109	103	100	99	-
2043	247	426	604	783	962	124	106	101	98	96	-
2044	241	415	589	762	936	120	104	98	95	94	-
2045	234	403	573	742	911	117	101	95	93	91	-
2046	228	392	557	721	886	114	98	93	90	89	-
2047	221	381	541	701	861	111	95	90	88	86	-
2048	215	370	525	680	835	107	92	88	85	84	-
2049	208	359	509	660	810	104	90	85	82	81	-
2050	202	348	493	639	785	101	87	82	80	79	-

	Future 60-MW BESS Costs ($/kW) - HIGH					Future 60-MW BESS Costs ($/kWh) - HIGH				
	2-hour	4-hour	6-hour	8-hour	10-hour	2-hour	4-hour	6-hour	8-hour	10-hour
2018										
2019	902	1.554	2.206	2.858	3.509	451	389	368	357	351
2020	879	1.513	2.148	2.783	3.417	439	378	358	348	342
2021	855	1.473	2.090	2.708	3.326	427	368	348	338	333
2022	831	1.432	2.032	2.633	3.234	416	358	339	329	323
2023	808	1.391	1.975	2.558	3.142	404	348	329	320	314
2024	784	1.350	1.917	2.483	3.050	392	338	319	310	305
2025	760	1.310	1.859	2.408	2.958	380	327	310	301	296
2026	743	1.279	1.816	2.352	2.889	371	320	303	294	289
2027	725	1.249	1.772	2.296	2.820	362	312	295	287	282
2028	707	1.218	1.729	2.240	2.750	354	304	288	280	275
2029	689	1.187	1.685	2.183	2.681	345	297	281	273	268
2030	672	1.157	1.642	2.127	2.612	336	289	274	266	261
2031	663	1.142	1.621	2.101	2.580	332	286	270	263	258
2032	655	1.128	1.601	2.074	2.547	327	282	267	259	255
2033	646	1.113	1.580	2.047	2.514	323	278	263	256	251
2034	638	1.099	1.560	2.021	2.482	319	275	260	253	248
2035	630	1.084	1.539	1.994	2.449	315	271	257	249	245
2036	621	1.070	1.519	1.968	2.416	311	268	253	246	242
2037	613	1.056	1.498	1.941	2.384	306	264	250	243	238
2038	604	1.041	1.478	1.914	2.351	302	260	246	239	235
2039	596	1.027	1.457	1.888	2.318	298	257	243	236	232
2040	588	1.012	1.437	1.861	2.286	294	253	239	233	229
2041	579	998	1.416	1.835	2.253	290	249	236	229	225
2042	571	983	1.396	1.808	2.221	285	246	233	226	222
2043	562	969	1.375	1.782	2.188	281	242	229	223	219
2044	554	954	1.355	1.755	2.155	277	239	226	219	216
2045	546	940	1.334	1.728	2.123	273	235	222	216	212
2046	537	925	1.314	1.702	2.090	269	231	219	213	209
2047	529	911	1.293	1.675	2.057	264	228	216	209	206
2048	520	897	1.273	1.649	2.025	260	224	212	206	202
2049	512	882	1.252	1.622	1.992	256	221	209	203	199
2050	504	868	1.231	1.595	1.959	252	217	205	199	196

Figure 29. CAPEX cost trajectory under conservative, moderate, and optimistic scenarios (NREL ATB, 2024) [8]

US Tariff Modifications on Chinese Imports (May 2024)

Category	Tariff	Date
Battery parts	Increase from 7.5% to 25%	August 1, 2024
Electric vehicles	Increase from 25% to 100%	August 1, 2024
Facemasks	Increase from 0 – 7.5% to 25%	August 1, 2024
Lithium-ion EV batteries	Increase from 7.5% to 25%	August 1, 2024
Lithium-ion non-EV batteries	Increase from 7.5% to 25%	January 1, 2026

Figure 30. U.S. tariff modifications affecting lithium-ion batteries (2024) [14]

Policy and Tax Structure

The ITC, available since the Inflation Reduction Act of 2022, [9] is applied directly to eligible CAPEX, reducing upfront capital requirements by 30%. Accelerated depreciation follows the U.S. MACRS five-year schedule (20%, 32%, 19.2%, 11.52%, 11.52%, 5.76%), significantly front-loading tax benefits and boosting after-tax IRR in early years.

Federal corporate tax is fixed at 28%, applied on EBIT. Property tax is modeled in two cases: high-tax (2.25%) without abatements and low-tax (1.5%) with abatements, reflecting county-level practices in Texas. These policy levers collectively shape the bankability of ERCOT storage projects.

Financing Assumptions

The project is modeled under a 65% debt / 35% equity structure, consistent with ERCOT utility-scale renewable projects. Debt tenor is capped at 10 years, shorter than the 15–20 year project lifetime, reflecting lender caution in ERCOT's BESS market. Debt service is set at a fixed 5.5% interest rate with straight-line amortization, although this number might decrease the upcoming years, due to recent news reflecting Powell's willingness to decrease interest rates. No explicit reserve accounts are modeled, but their cost is embedded in CAPEX.

Revenue Structure

Revenues are sourced directly from the dispatch model outputs. The base case assumes DAM-only arbitrage, charging during the two cheapest consecutive hours and discharging during the two most expensive consecutive hours. An optional DAM-RT hybrid mode is also included to represent upside potential if predictive algorithms enable optimal switching between DAM and RTM.

Ancillary service revenues are excluded from the base case, reflecting increasing saturation in ERCOT's ancillary markets. Instead, the model applies a conservative assumption of energy arbitrage as the main driver, with ancillary services treated as optional upside. Inflation is modeled at 1.5% annually, applied equally to revenues and OPEX.

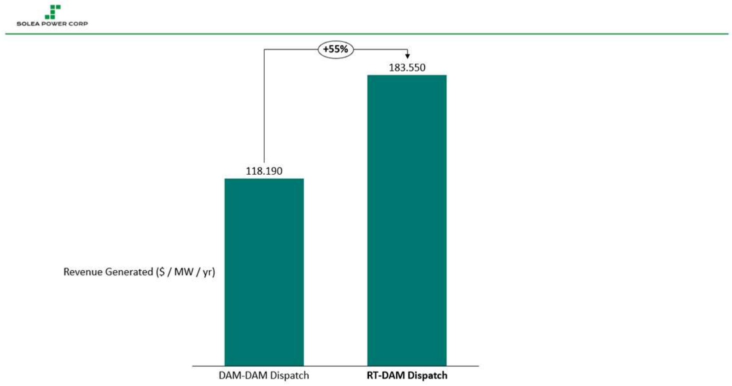


Figure 31. Example of revenue uplift /MW/yr from base DAM case to RT-DAM case

Performance and Degradation

The model incorporates annual performance losses to account for technical degradation. Initial RTE is 93%, declining by 1% per year, while capacity fade is set at 1.95% annually at 95% DoD. HVAC and auxiliary consumption are represented as a flat 6% of gross revenue, while system availability is set at 99%. Together, these parameters reduce long-term cash flows, particularly after Year 10, and underscore the importance of maximizing early equity returns.

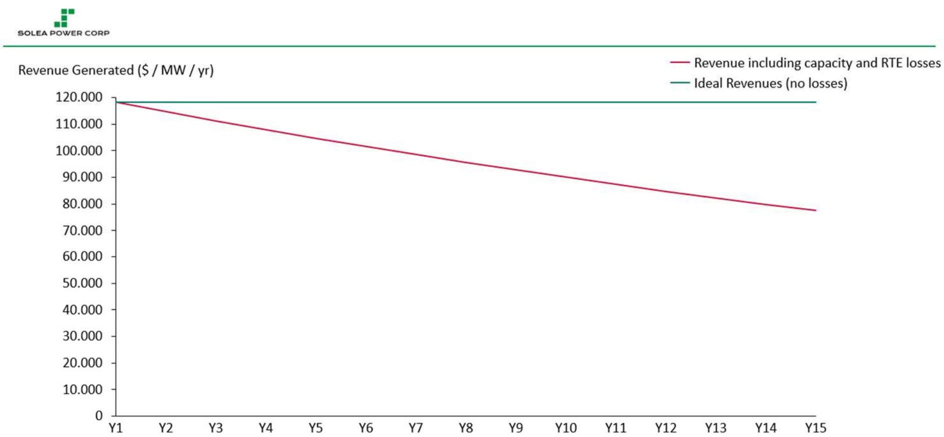


Figure 32. Impact of degradation and auxiliary loads on annual revenue per MW

Outputs and KPIs

The model generates a consolidated KPI dashboard including:

- Unlevered Project IRR (base case: ~4–5%)
- Levered Shareholder IRR (base case: ~6–7%)
- Net Present Value (NPV) at a market-consistent WACC
- Payback period for both project and equity cash flows

Outputs are visualized via a waterfall chart (gross revenues to equity cash flows), a cumulative cash flow curve (payback year), and a sensitivity tornado chart (showing IRR sensitivity to CAPEX, degradation, and property tax). These outputs make financial risks and opportunities transparent, supporting investment decision-making at nodal level.

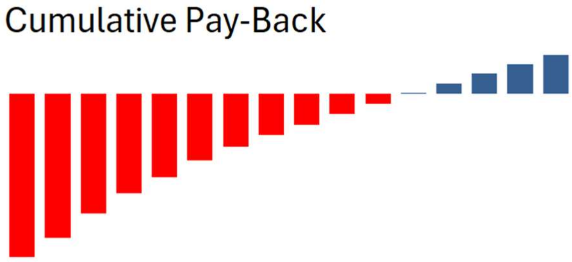


Figure 33. Example of cumulative equity cash flow over project lifetime

By embedding ERCOT's nodal pricing directly into a full project finance framework, this model bridges the gap between technical feasibility and investor decision-making. It enables rapid testing of multiple scenarios, from conservative CAPEX to DAM-RT arbitrage, while ensuring that degradation, policy, and financing realities are captured. The result is a flexible decision-support tool that balances technical accuracy with investor-grade financial outputs.

4. Results and Discussion

The results chapter applies the techno-economic model to real ERCOT nodes, illustrating how nodal conditions, solar resources, and price volatility shape the financial viability of BESS projects. Two representative case studies are presented: Pamplona (Houston Hub) and Santa Monica (North Hub). These were selected because they align with ongoing project development interests while providing contrasting market conditions. Houston is characterized by higher volatility and stronger solar resources, though with land and interconnection constraints, whereas the North Hub reflects a more stable grid region with lower volatility and modest solar yields.

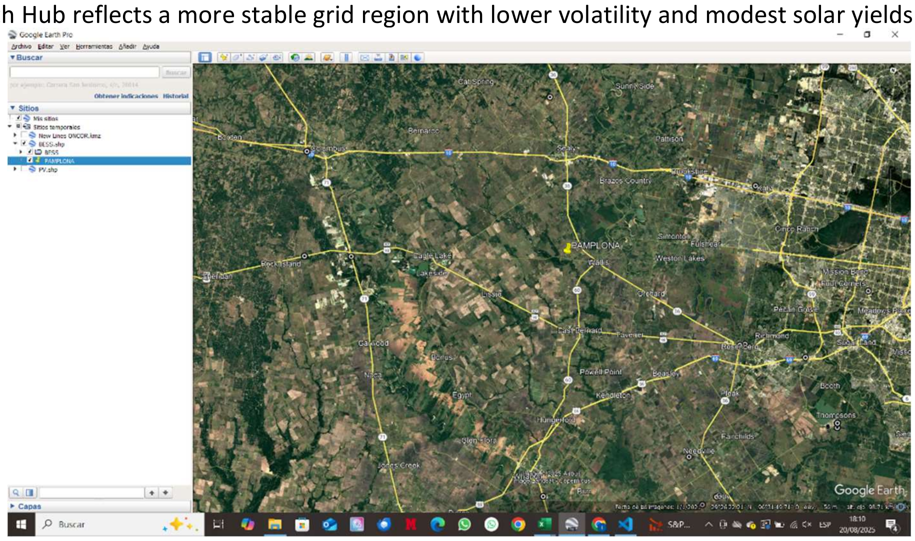


Figure 34. Location of the Pamplona node west of Houston

Together, these case studies demonstrate how identical BESS configurations can produce markedly different financial outcomes depending on nodal context. Section 4.2 expands this analysis to a hub-wide benchmarking, while Section 4.3 introduces sensitivity testing to explore robustness under various assumptions.

4.1 Base Case Node Analysis

This section evaluates the model's financial outputs at the node level. For each site, annual revenues, internal rates of return (IRRs), and payback periods are reported, followed by a direct comparison highlighting the role of location in project feasibility.

4.1.1 Pamplona (Houston Hub)

Pamplona ranks among the stronger nodes in ERCOT due to its high price spreads and volatility, which directly enhance arbitrage revenues. Under base case assumptions, the model estimates annual revenues of $89,412 per MW system, corresponding to a project IRR of 4.93% (unlevered) and shareholder IRR of 6.0% (levered). Payback periods are 10 years at the project level and 12 years at the equity level. While modest by absolute standards, these figures are attractive for a DAM-only strategy, especially relative to ERCOT averages.

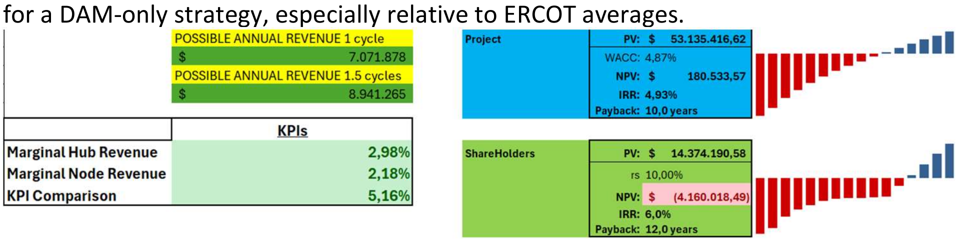


Figure 35. Pamplona Node (GEB_138A) Summary Sheet Results

From a solar perspective, Pamplona's average solar price was $49.71/MWh, just below the Houston Hub average ($50.06/MWh). Curtailment is negligible (2 hours per year), which means co-location is not driven by curtailment avoidance. However, if sufficient land is available, EPC and interconnection synergies may still make solar-plus-storage development viable.

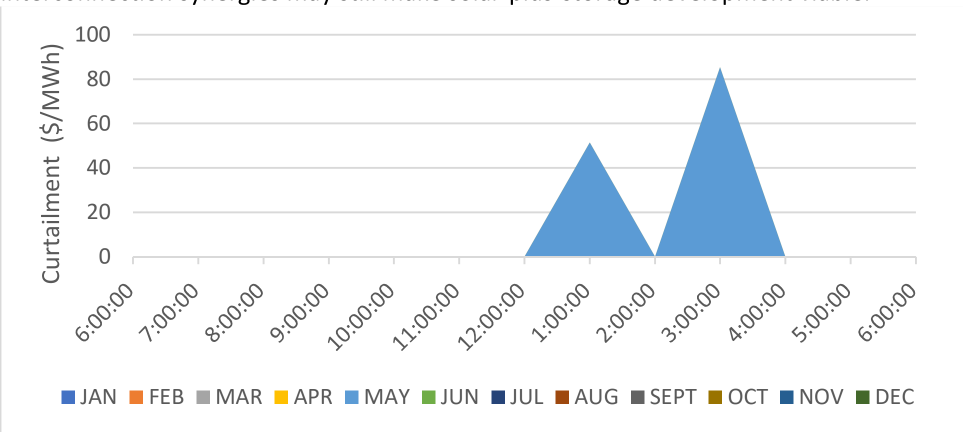


Figure 36. Curtailment incidence at Pamplona, showing only two curtailed hours in a representative day [23]

4.1.2 Santa Monica (North Hub)

Santa Monica provides a useful counterpoint. Annual revenues were $85,247 per MW system, nearly $4,200 less than Pamplona per MW-year, leading to weaker economics: project IRR of 3.95% and shareholder IRR of 3.9%. Payback periods extend to 11 years (project) and 13 years (shareholders), reflecting thinner margins.

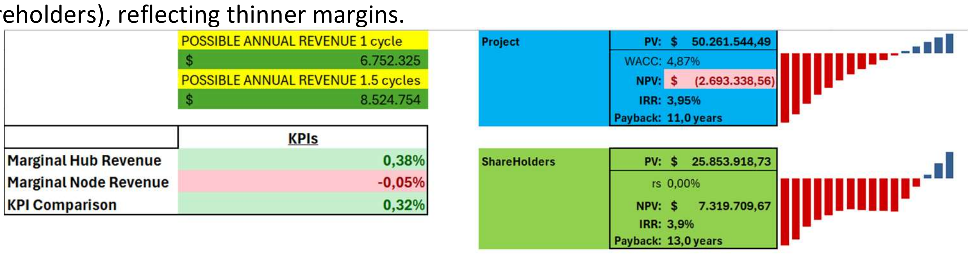


Figure 37. Summary sheet of financial results for the Santa Monica node [23]

Interestingly, Santa Monica's average solar price of $45.84/MWh slightly exceeded the North Hub average ($45.49/MWh), making it attractive for solar development even if BESS economics underperform. Indeed, the node ultimately hosted a solar-only project, illustrating how nodal dynamics may favor different technologies. Curtailment is virtually zero, meaning co-location would provide little incremental value beyond EPC or interconnection synergies.

4.1.3 Comparative Insights

The comparison highlights the centrality of nodal volatility. Pamplona's higher spreads underpin stronger BESS revenues and returns, while Santa Monica's thinner spreads produce weaker economics despite comparable solar attractiveness.

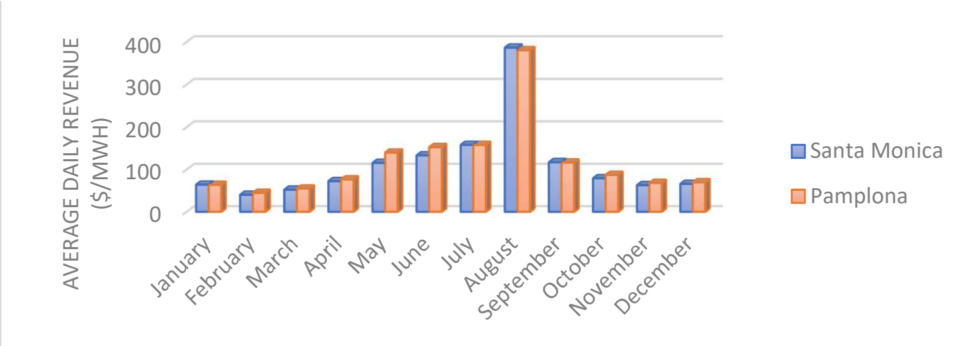


Figure 38. Monthly average daily revenues at Pamplona vs. Santa Monica, showing consistently higher spreads in Pamplona

In both nodes, curtailment is negligible, so co-location benefits hinge more on synergies than avoided losses. This differs markedly from West Texas, where curtailment can reach hundreds of hours annually due to congestion, making co-location a primary driver of value.

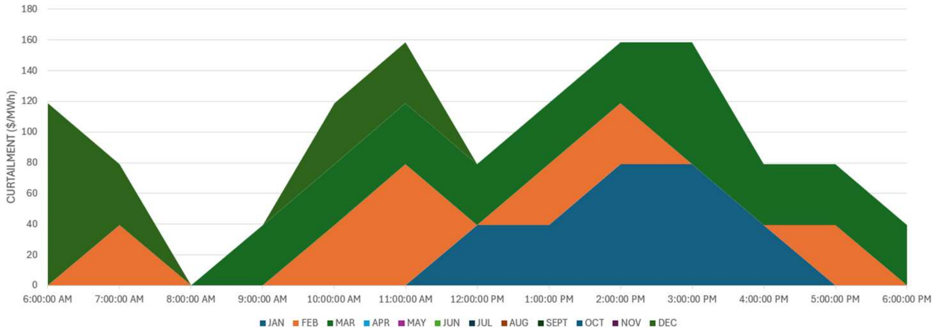


Figure 39. Curtailment example in a representative West Texas node (DUBLIN_8), showing significantly higher lost hours

Table 4 consolidates financial and technical metrics, reinforcing that Pamplona outperforms Santa Monica for standalone storage under DAM-only dispatch.

Table 4. Comparative summary of Pamplona vs. Santa Monica BESS results

Metric	Pamplona (Houston Hub)	Santa Monica (North Hub)
Annual Revenues Y1 ($/yr, 100 MW / 200 MWh)	$894,127	$852,470
Project IRR (Unlevered)	4.93%	3.95%
Shareholder IRR (Levered)	6.0%	3.9%
Payback Period (Project)	10 years	11 years
Payback Period (Shareholders)	12 years	13 years
Average Solar Price ($/MWh)	49.71 (< Hub avg. 50.06)	45.84 (> Hub avg. 45.49)
Curtailment Hours (per year)	2	0
Solar Feasibility	Strong but secondary (EPC/interconnection synergies)	Attractive solar-only
Co-location Potential	Conditional (excess land)	Minimal
Volatility Profile	High, strong spreads	Moderate, thinner spreads

4.2 ERCOT-Wide Benchmarking and Nodal Competitiveness

The comparative analysis between Pamplona and Santa Monica underscores the decisive role of nodal conditions in shaping BESS outcomes. While both sites displayed low curtailment, their revenue and IRR profiles diverged due to volatility and hub-specific dynamics. To move beyond case studies, this section benchmarks revenues across ERCOT's 17,000+ nodes, providing a system-wide perspective on storage economics and identifying where opportunities are concentrated.

4.2.1 Hub-Level Benchmarking

ERCOT is organized into six hubs: North, South, Houston, West, Coastal, and Panhandle. This analysis focuses on the first four, where most BESS development occurs. Each hub exhibits distinct price seasonality, with West tending to outperform in winter months and Houston and North showing stronger revenues in summer.

At the ERCOT-wide level, the average revenue benchmark is $84,971/MW-year, which serves as a reference point for above- and below-average hubs.

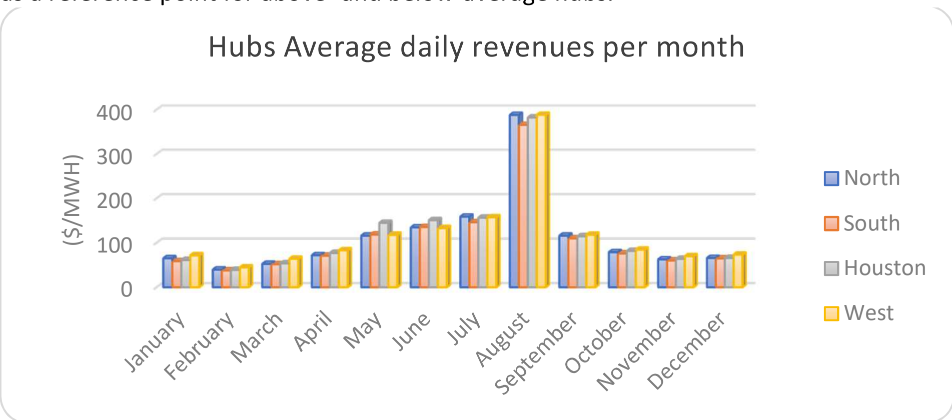


Figure 40. Average annual revenues across ERCOT Main Hubs, excluding Coastal and Panhandle

The West Hub leads with $90,497/MW-year, more than 6% above the ERCOT average. This reflects strong volatility and arbitrage spreads, driven by high solar penetration and frequent congestion. However, West also suffers from severe curtailment due to wind penetration and transmission bottlenecks. Co-located storage offers clear value in this hub, enabling curtailed energy to be absorbed and later sold into evening peaks.

The Houston Hub follows with $87,505/MW-year. Its revenues are supported by high demand density, scarcity pricing events, and frequent weather-driven volatility. However, development here is constrained by limited land availability and interconnection bottlenecks. For projects that overcome these barriers, Houston remains one of ERCOT's strongest arbitrage opportunities.

The North Hub averages $85,290/MW-year, close to the ERCOT-wide mean. While spreads are thinner than in Houston or West, lower volatility also reduces downside risk. This stability may appeal to risk-averse investors seeking predictable returns, making high-performing nodes in the North Hub particularly attractive.

The South Hub trails at $81,906/MW-year, about 3.6% below the ERCOT mean. With lower demand concentration and growing congestion, standalone storage is less attractive here. Instead, co-location with solar provides a more compelling case, enabling capture of curtailed energy that would otherwise be lost.

Taken together, hub-level results confirm that location is decisive for feasibility. West and Houston offer the highest standalone economics, albeit constrained by curtailment and siting challenges, while North and South trade profitability for greater predictability or co-location potential.

4.2.2 Node Ranking and Relative KPIs

To complement hub averages, node-level KPIs provide a more granular view. Two indicators are applied:

- **Marginal Hub Revenue:** deviation of the hub from the ERCOT-wide benchmark.
- **Marginal Node Revenue:** deviation of a given node from its hub average.

This dual KPI model distinguishes whether competitiveness is hub-driven, node-driven, or both.

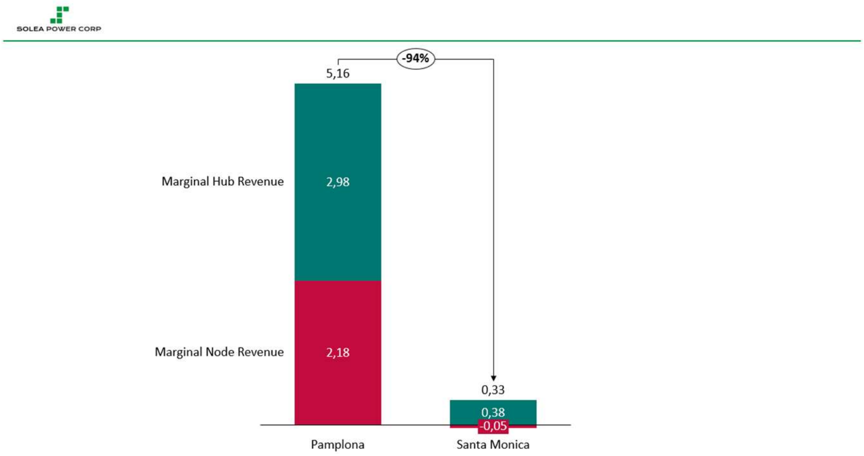


Figure 41. Comparative KPI premiums for Pamplona and Santa Monica nodes relative to hub and ERCOT benchmarks

Pamplona generates $89,412/MW-year, which is 2.2% above the Houston Hub average and 5.2% above the ERCOT-wide mean. This reinforces Houston's appeal for arbitrage and positions Pamplona as a standout location despite local land and interconnection constraints.

By contrast, Santa Monica earns $85,247/MW-year, almost exactly at the North Hub average (-0.05%) and only marginally above the ERCOT mean (+0.4%). While not a top arbitrage performer, its relatively strong solar price compared to the hub average makes it attractive for solar-only or hybrid development.

Three insights emerge:

- **Node-level differences matter** - even within the same hub, spreads can shift project economics by several percentage points.
- **Hub averages conceal dispersion** - standout nodes like Pamplona outperform their peers, while others barely reach average levels.
- **ERCOT-wide benchmarking is critical** - a node's competitiveness must be measured against the system-wide mean to establish a consistent feasibility baseline.

These KPIs allow developers to rank nodes directly against proven projects. If a candidate node consistently outperforms known viable locations, it represents a strong development lead. This reinforces the need for granular nodal modeling, rather than reliance on hub-level averages, to guide site selection.

4.3 Sensitivity Analysis (Pamplona Case Study)

To assess the robustness of the developed techno-economic model, a sensitivity analysis was conducted on the Pamplona node in the Houston Hub. Pamplona was chosen as the reference point given its strong base-case performance and representativeness of volatile ERCOT conditions. By varying one parameter at a time while holding all others constant, the analysis identifies the operational and financial assumptions with the greatest influence on project feasibility. Results are expressed as changes in annual revenues, project IRR, shareholder IRR, and payback period relative to the base case.

4.3.1 Day-Ahead vs. DAM–RT Dispatch

Dispatch strategy emerged as the most influential factor. In the Day-Ahead Market (DAM) only case, Year 1 revenues for a 100 MW / 200 MWh installation reached $8.94 million, yielding a project IRR of 4.9% and shareholder IRR of 6.0%. When shifting to an idealized DAM–RT strategy, revenues rose to $14.68 million, a 64% uplift.

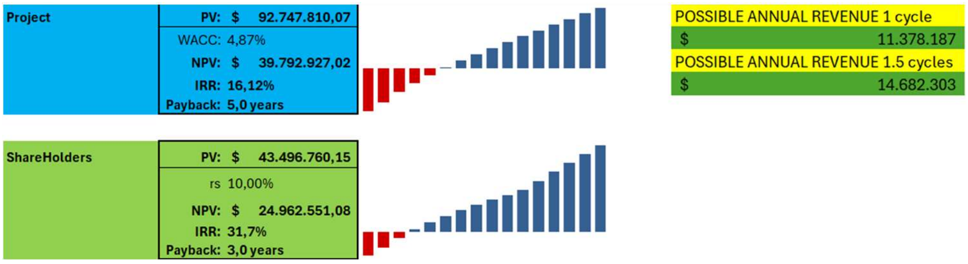


Figure 42. Pamplona simulated DAM–RT dispatch scenario

This increase lifted project IRR to 16.1% and shareholder IRR to 31.7%, while halving payback periods to 3–5 years. Although the DAM-RT scenario assumes perfect foresight of real-time peaks, being technically not possible, it highlights the transformative potential of predictive dispatch tools such as machine learning-enabled forecasting. Even partial capture of this upside would materially strengthen BESS economics in ERCOT.

4.3.2 CAPEX Scenarios

Capital expenditure assumptions are another decisive factor. Using NREL's cost projections, three CAPEX tiers were tested for a 2027 commissioning date:

Optimistic case (473 $/kW): IRR rose to 15.5% (project) and 30.1% (shareholders), with payback shortened to six and three years, respectively.

Moderate case (756 $/kW): Base case reference, yielding IRRs of 4.9% and 6.0%.

Conservative case (844 $/kW): IRRs fell sharply to 2.7% and 1.3%, extending payback periods beyond 12 years.

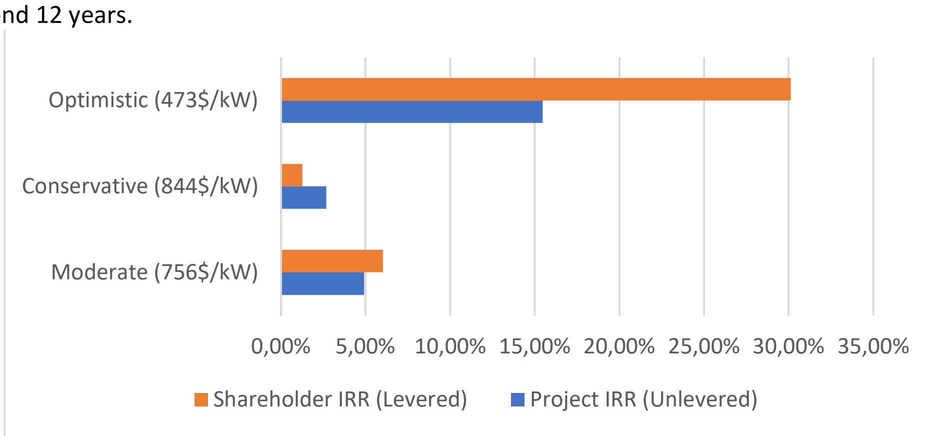


Figure 43. IRR shifts under Optimistic, Moderate, and Conservative NREL CAPEX scenarios

These results show that CAPEX reductions remain a structural enabler for ERCOT BESS projects, much like the early solar PV industry. Without continued cost declines or federal incentives such as the 30% ITC, standalone arbitrage projects risk falling into negative NPV territory.

4.3.3 Technical Parameters

While less decisive than market strategy or CAPEX, technical parameters significantly shape financial performance:

- **Cycle count:** Reducing cycling from 1.5 to 1 cycle per day (extending lifetime from 15 to 20 years) lowered Year 1 revenues from \$8.94m to \$7.07m (-21%). Although lifetime is extended, investors generally prefer the higher near-term cash flows of 1.5 cycles/day, which mitigate risk through faster payback.
- **Depth of discharge (DoD):** At 95% DoD, IRRs are maximized. Reducing to 80% cut revenues by 15.8% (\$7.53m), lowering IRRs to 3.8% approximately. At 65%, revenues dropped by 31.7% (\$6.11m), with IRRs below 3%. While shallower cycling slows degradation, the economic penalty outweighs the technical gain.
- **Round-trip efficiency (RTE):** Raising efficiency from 93% to 95% increased revenues modestly to \$9.15m (+2.3%), lifting IRRs to 5.4% and 7.0%. Reducing RTE to 91% had the opposite effect, reducing revenues to \$8.74m.

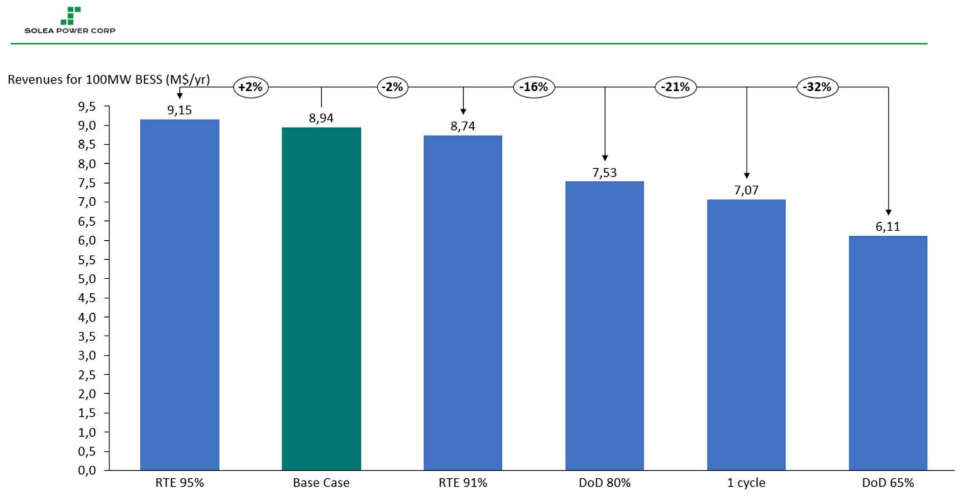


Figure 44. Year 1 revenues under varying technical parameters

Overall, technical refinements act as value optimizers, improving margins but not fundamentally altering feasibility. Their impact is most effective when paired with stronger levers like DAM–RT dispatch or lower CAPEX.

4.3.4 Synthesis

The sensitivity analysis confirms that location and dispatch strategy dominate BESS viability in ERCOT, with capital costs and ITC support as structural enablers. Technical parameters such as DoD and RTE refine outcomes but do not transform unviable projects into viable ones. In particular, the transition from DAM-only to DAM-RT dispatch can more than triple shareholder IRR, underscoring the importance of predictive trading strategies for the next generation of ERCOT storage projects.

Table 5. Sensitivity results for Pamplona node under alternative assumptions

Scenario	Year 1 Revenue ($m)	Project IRR (%)	Shareholder IRR (%)	Payback (Years)
Base Case (DAM, 93% RTE, 95% DoD, Mid CAPEX $756/kW)	8.94	4.9	6.0	10
DAM–RT Dispatch	14.68	16.1	31.7	3–5
Optimistic CAPEX ($473/kW)	8.94	15.5	30.1	3–6
Conservative CAPEX ($844/kW)	8.94	2.7	1.3	12+
1 Cycle/Day	7.07	3.8	3.8	12
80% DoD	7.53	3.8	3.6	13
65% DoD	6.11	2.7	2.0	16
95% RTE	9.15	5.4	7.0	10
91% RTE	8.74	4.5	5.0	11

5. Conclusions

Battery Energy Storage Systems (BESS) have emerged as a cornerstone technology for ensuring reliability in renewable-heavy power systems. In ERCOT, where volatility is amplified by the absence of a capacity market and limited interconnection with neighboring grids, storage provides a clear pathway to stability and profitability. Cost declines, regulatory incentives such as the Inflation Reduction Act (IRA), and advances in dispatch optimization position storage for accelerated growth over the next decade, growth that will also be seen in ERCOT demand peaks, further increasing BESS' possibilities to be viable in many locations within Texas.

The methodology developed in this thesis integrated SQL, Python, and Excel/VBA into a scalable techno-economic model, enabling nodal analysis across ERCOT's 17,000+ settlement points.

By combining technical realism, degradation, efficiency losses, and seasonal cycling, with financial modeling, the model bridges the gap between granular price signals and investment decision-making. Its modular design makes it both rigorous and accessible, providing actionable insights for developers and investors involved.

Results confirm that location and market strategy are decisive for project feasibility. Hub-level benchmarking shows West ERCOT as the most profitable region for arbitrage, but constrained by congestion and curtailment. Houston follows closely, offering high volatility and strong arbitrage opportunities, while North and South hubs trade profitability for stability, being the latter even less profitable. At the nodal scale, Pamplona (Houston Hub) outperformed Santa Monica (North Hub), highlighting how small locational differences drive divergence in IRR and payback. This reinforces the necessity of site-specific modeling rather than relying solely on hub averages.

The sensitivity analysis further demonstrated that dispatch strategy and CAPEX assumptions dominate BESS viability. Transitioning from DAM-only to an idealized DAM-RT strategy tripled shareholder IRRs, cutting payback from over 10 years to as few as 3. Similarly, optimistic CAPEX scenarios lifted IRRs above 15%, while conservative costs pushed projects toward unviability. Technical parameters such as depth of discharge (DoD) or round-trip efficiency (RTE) acted more as fine-tuning levers, shaping margins but not fundamentally altering outcomes.

Despite the promise, limitations remain. Ancillary services, real-time participation, and stochastic elements such as weather events were excluded from the base case, making the analysis deliberately conservative. Assumptions on fixed HVAC or inner cooling loads, average degradation rates, and static tax treatments also simplified reality, though without obscuring the key dynamics at play. These boundaries mark natural points for future work: integrating predictive DAM-RT dispatch, incorporating ancillary services revenues, and dynamically modeling ERCOT's interconnection queue to anticipate cannibalization effects.

In summary, BESS in ERCOT stand at a critical juncture. Properly sited, competitively built, and strategically dispatched, storage projects can deliver meaningful investor returns while simultaneously stabilizing one of the most volatile power markets in the world. This thesis demonstrates that nodal-level modeling is not only possible but essential, offering a decision-support tool that balances technical fidelity with financial realism. Beyond its academic contribution, the model has already delivered tangible value to Solea Power Corp., where it has been applied as a low-cost preliminary screening tool to prioritize nodes before investing in costly interconnection studies. By saving both time and resources, the model has become a practical enabler for a startup environment with limited capacity but ambitious stakeholders. Future work should focus on predictive analytics and expanded revenue stacking, but the results here already provide a foundation for both project developers and policymakers. Storage in ERCOT is no longer a peripheral opportunity, it's central to the market and grid's evolution.

6. Patents

No patent is associated to this work, though it could be solicited in the future if need be.

Funding: This research received no external funding

Data Availability Statement: LMP DAM and RT daily data per month and year can be found here: ERCOT. Market operations and nodal pricing documentation. Electric Reliability Council of Texas. Available online: https://www.ercot.com

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Conflicts of Interest: The authors declare no conflict of interest

Appendix A – BESS and Summary Sheet and Financial Sheet

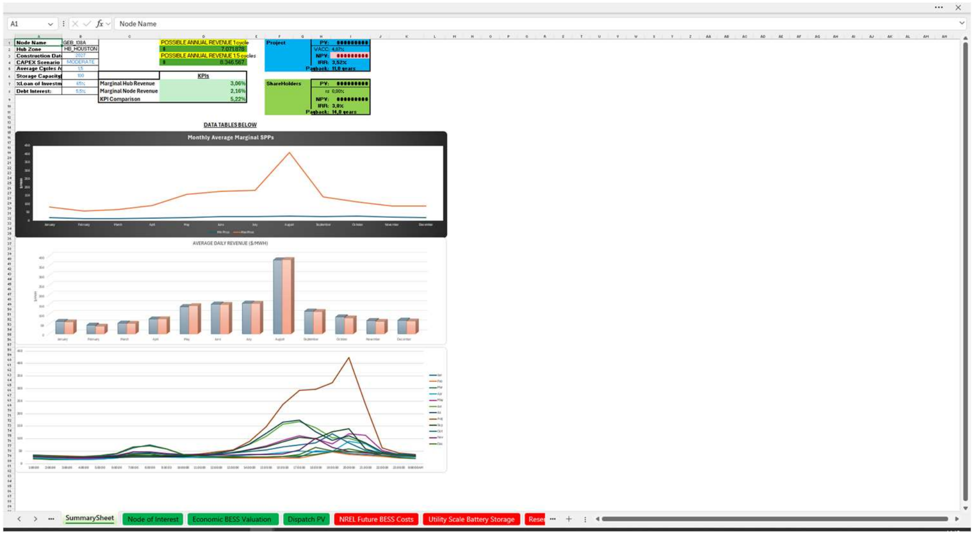

Figure A1. BESS Model Summary Sheet

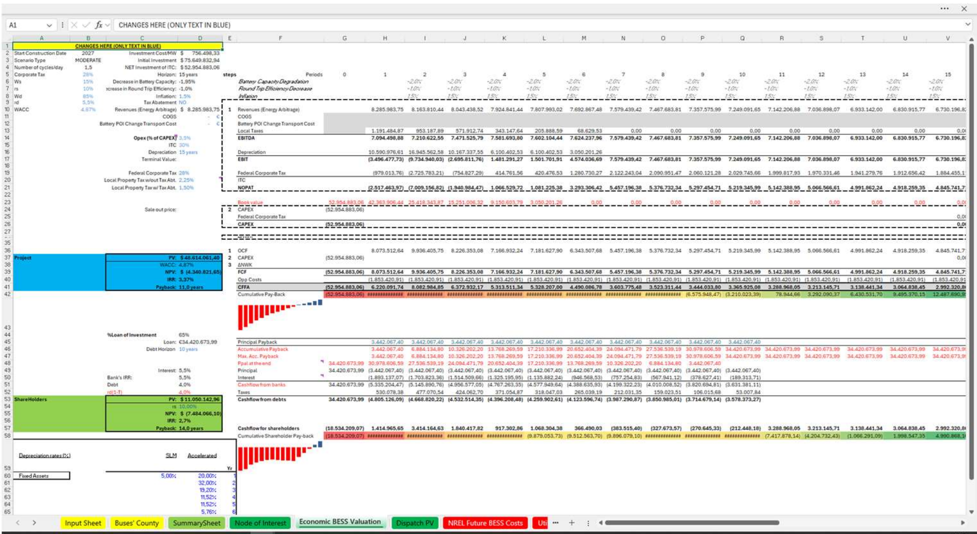

Figure A2. BESS Model Financial Sheet

Appendix B - Curtailment Model

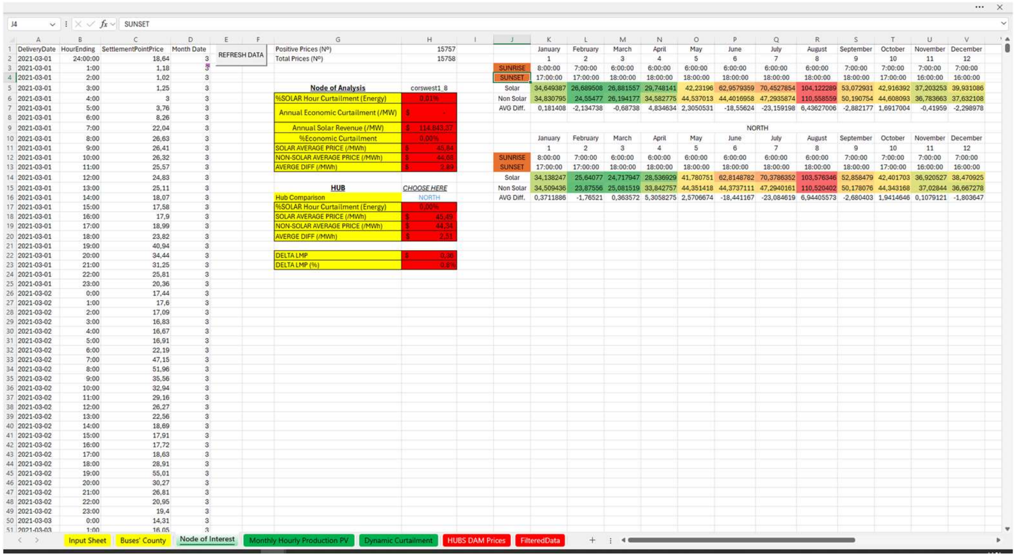

Figure B1. Curtailment Model Summary Sheet

References

1. ERCOT. *Market operations and nodal pricing documentation*. Electric Reliability Council of Texas. Available online: https://www.ercot.com
2. U.S. Energy Information Administration (EIA). *Electric Power Monthly: Texas renewable generation*. Available online: https://www.eia.gov/electricity/monthly/
3. Modo Energy. *ERCOT BESS Index: Battery revenues in 2023 surpass $1.2bn; new ECRS service shakes up market*. Available online: https://modoenergy.com/research/ercot-battery-energy-storage-systems-annual-revenues-2023-bess-index-ancillary-services-arbitrage-ecrs
4. U.S. Energy Information Administration (EIA). *Winter storm affected Texas energy prices and demand*. Available online: https://www.eia.gov/todayinenergy/detail.php?id=47876
5. International Energy Agency (IEA). *Global Energy Storage Report 2024*. Available online: https://www.iea.org/reports/global-energy-storage
6. Octopart. *Lithium-ion cell composition*. Available online: https://octopart.com/blog/archives/2019/11/lithium-ion-battery-basics
7. Grimaldi, A.; Minuto, F.D.; Perol, A.; Casagrande, S.; Lanzini, A. *Ageing and energy performance analysis of a utility-scale lithium-ion battery for power grid applications through a data-driven empirical modelling approach*. Journal of Energy Storage 2023, 65, 107232. https://doi.org/10.1016/j.est.2023.107232.
8. National Renewable Energy Laboratory (NREL). *Utility-Scale Battery Storage — 2024 Annual Technology Baseline (ATB)*. Available online: https://atb.nrel.gov/electricity/2024/index
9. U.S. Congress. *Inflation Reduction Act of 2022*, Public Law No. 117-169. Available online: https://www.congress.gov/bill/117th-congress/house-bill/5376
10. BCC Research. *Flow batteries: The future of energy storage*. Available online: https://blog.bccresearch.com/flow-batteries-the-future-of-energy-storage
11. Infinite Power. *What are liquid flow batteries and their advantages?* Available online: https://www.infinitepowerht.com/what-are-liquid-flow-batteries-and-their-advantages.html
12. Federal Emergency Management Agency (FEMA). *Emerging hazards: Battery energy storage system fires*. U.S. Department of Homeland Security. Available online: https://www.fema.gov/case-study/emerging-hazards-battery-energy-storage-system-fires
13. Modo Energy. *How ERCOT BESSs use Day-Ahead and Real-Time prices to maximize revenue*. Available online: https://modoenergy.com/research/ercot-dart-optimization-explainer-day-ahead-real-time-trading-dart-spread-settlement-energy-arbitrage-battery-energy-storage
14. U.S. International Trade Administration (ITA). *Section 301 Tariffs on Chinese Imports: Lithium-ion Batteries and Components*. Available online: https://www.trade.gov/section-301-tariffs
15. U.S. Internal Revenue Service (IRS). *Modified Accelerated Cost Recovery System (MACRS) Depreciation Schedules*. Available online: https://www.irs.gov/businesses/depreciation