COMILLAS
UNIVERSIDAD PONTIFICIA
ICAI

UNIVERSITY MASTER'S DEGREE IN INDUSTRIAL ENGINEERING

MASTER'S THESIS

Optimization of BESS projects & Dispatch Strategies in the ERCOT Market

Author: Iñigo Fernandez de la Concha Rebollo

Director: Iñigo Sangroniz Ojer

28 August de 2025

Madrid

Declaro, bajo mi responsabilidad, que el Proyecto presentado con el título

Optimization of BESS projects & Dispatch Strategies in the ERCOT Market - ICAI de la Universidad Pontificia Comillas en el

curso académico 2024/2025 es de mi autoría, original e inédito y

no ha sido presentado con anterioridad a otros efectos.

El Proyecto no es plagio de otro, ni total ni parcialmente y la información que ha sido

tomada de otros documentos está debidamente referenciada.

I.F.C

Fdo.: Iñigo Fernandez de la Concha Rebollo Fecha: 27/08/2025

Autorizada la entrega del proyecto

EL DIRECTOR DEL PROYECTO

Firmado por
SANGRONIZ OJER
IÑIGO -
***1778** el
día 28/08/2025

Fdo.: Iñigo Sangróniz Ojer Fecha: 28/08/2025

COMILLAS
UNIVERSIDAD PONTIFICIA

ICAI

UNIVERSITY MASTER'S DEGREE IN INDUSTRIAL ENGINEERING

MASTER'S THESIS

Optimization of BESS projects & Dispatch Strategies in the ERCOT Market

Author: Iñigo Fernandez de la Concha Rebollo

Director: Iñigo Sangroniz Ojer

28 August de 2025

Madrid

Acknowledgements

The year I spent at Solea Power Corporation gave me the chance to meet very interesting and nice people. I would especially like to thank all the development of this model to Iñigo Sangroniz, who helped me create my own roadmap into developing this model and offered to help anytime I needed a hand. I also must thank the mastermind of this autonomous contribution to the company, Terio Escudero, COO at Solea Power. Without his trust in letting me figure things out and develop something that's been impactful to the company, I wouldn't have been able to give it all my best on this project. Thanks to everyone in the company to trust me in the process, and thanks to my family for being so devoted and interested in this project, everyone has contributed to this project to some level, and I couldn't have done it better without them.

Thank you!

OPTIMIZACIÓN DE PROYECTOS Y ESTRATEGIAS DE DESPACHO DE BESS EN EL MERCADO ERCOT

Autor: Fernandez de la Concha Rebollo, Iñigo
Director: Sangroniz Ojer, Iñigo
Entidad Colaboradora: Solea Power Corp. SA

RESUMEN DEL PROYECTO

Los Battery Energy Storage Systems (BESS) se están consolidando rápidamente como tecnologías fundamentales en los sistemas eléctricos modernos, especialmente en mercados con alta penetración renovable y gran volatilidad de precios. Un ejemplo óptimo es el de Electric Reliability Council of Texas (ERCOT), que gestiona uno de los mercados eléctricos más dinámicos y singulares del mundo. ERCOT opera bajo un esquema "energy-only", sin mercado de capacidad centralizado y con mínima interconexión con redes vecinas. Este diseño intensifica el papel de las señales de precio para equilibrar oferta y demanda, generando elevada volatilidad, frecuentes episodios de curtailment en la generación renovable y exposición a eventos extremos como la tormenta invernal de 2021. En este contexto, los BESS ofrecen un doble beneficio: proporcionan a los inversores oportunidades de arbitraje energético y servicios de red, al tiempo que refuerzan la resiliencia de ERCOT absorbiendo excedentes renovables y cubriendo picos de demanda. Para desarrolladores como Solea Power Corp., una startup con sede en Houston que busca expandirse del solar al almacenamiento, estas oportunidades se ven matizadas por la elevada incertidumbre y los costes prohibitivos de los estudios preliminares. De allí surge la motivación de esta tesis: crear un modelo tecno-económico sólido y eficiente en recursos que permita evaluar la viabilidad de BESS a nivel nodal en ERCOT y guiar decisiones de inversión antes de comprometerse a estudios de interconexión completos.

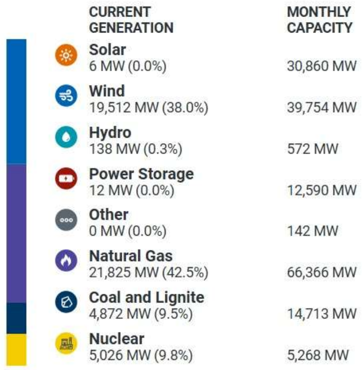


Figura A1. Mezcla de generación en ERCOT 2025

El objetivo principal de este trabajo es diseñar y aplicar un marco de modelado tecno-económico capaz de simular el rendimiento y la rentabilidad de un BESS de 2 horas de ion-litio en los más de 17,000 nodos de precios de ERCOT. El modelo integra tres dimensiones clave:

I. Parámetros técnicos como "depth of discharge" (DoD), "state of charge" (SoC), "round-trip efficiency" (RTE) y tasas de degradación anual.

II. Lógica de despacho basada en diferenciales del "Day-Ahead Market" (DAM), con extensión a estrategias híbridas DAM-RTM.
III. Una capa financiera de "project finance" que incluye CAPEX, OPEX, el "Investment Tax Credit" (ITC) del 30% para almacenamiento independiente, depreciación acelerada MACRS, y estructura deuda-capital.

De forma paralela, se desarrolló un modelo de curtailment para evaluar el valor añadido de la hibridación solar + almacenamiento, particularmente en regiones como el oeste de Texas donde los niveles de curtailment son elevados. En conjunto, estos componentes conforman una herramienta escalable y de nivel inversor para apoyar el desarrollo de proyectos de almacenamiento.

El modelo se implementó mediante una arquitectura híbrida de datos y simulación. El conjunto de precios DAM de ERCOT (más de 3.9 millones de valores horarios entre marzo de 2021 y septiembre de 2024) fue estructurado en una base de datos SQL para lograr una eficiencia óptima. Python actuó como intermediario, recuperando precios nodales y transfiriéndolos a un motor de despacho en Excel/VBA, donde se simularon ciclos de carga/descarga diarios bajo supuestos estacionales (1 ciclo/día en verano, 2 ciclos/día en invierno). La degradación se aplicó externamente para mantener modularidad, y la capa financiera se integró directamente en Excel, asegurando accesibilidad para usuarios no técnicos. Este flujo SQL–Python–Excel redujo tiempos de simulación de más de 5 minutos por nodo a menos de 1, permitiendo un benchmarking completo de ERCOT de forma transparente y simple.

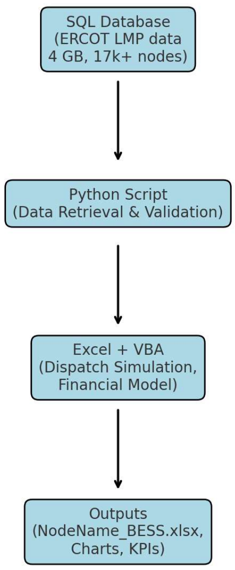


Figura A2. Arquitectura del modelo tecno-económico de BESS

En la sección de resultados, el modelo se aplicó primero a dos casos de estudio: Pamplona (Houston Hub) y Santa Monica (North Hub). Pamplona se benefició de mayor volatilidad y "spreads", generando ingresos del primer año de $89,412/MW y IRRs de 4.9% (proyecto) y 6.0% (accionistas). Santa Monica, en contraste, alcanzó $85,247/MW y retornos más débiles (3.9% aprox. en ambos IRRs), reflejando spreads menos pronunciados pese a precios solares competitivos. Estos casos subrayan la necesidad de análisis a nivel nodal, ya que los promedios de hub ocultan diferencias relevantes en rentabilidad.

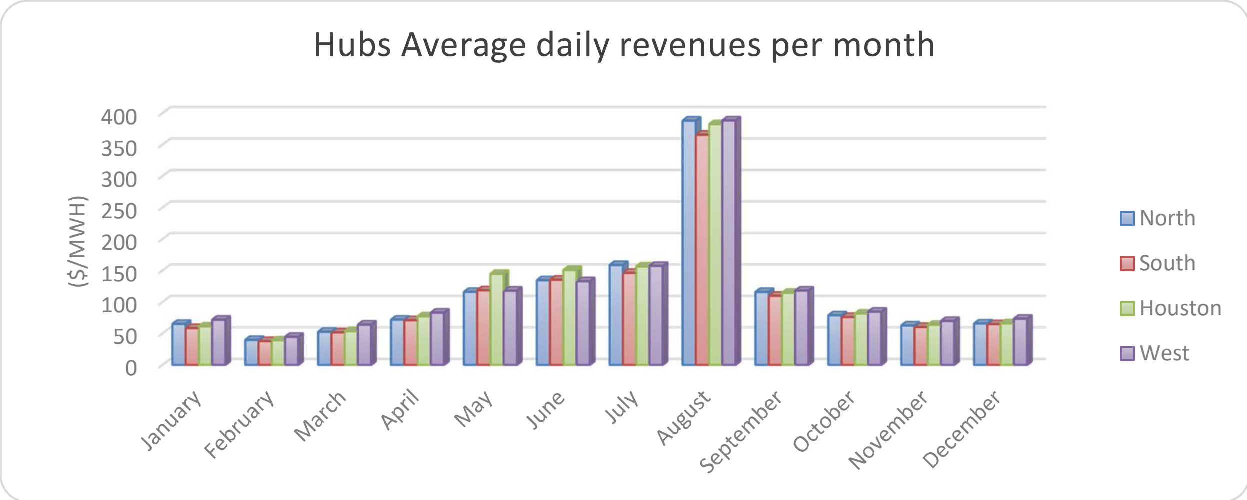


Figura A3. Ingresos anuales promedio por hub principal de ERCOT (excluyendo Coastal y Panhandle)

A escala de hub, el West Hub lideró con $90,497/MW-año, impulsado por volatilidad, pero limitado por curtailment y congestión. Houston siguió con $87,505/MW-año, atractivo para arbitraje, pero con desafíos de interconexión y suelo disponible. Los hubs Norte y Sur ofrecieron menores ingresos absolutos, pero con más estabilidad (Norte) o mayor potencial de hibridación (Sur). Estos resultados refuerzan el papel decisivo de la ubicación en la viabilidad de proyectos BESS.

El análisis de sensibilidad mostró que la estrategia de despacho y el CAPEX son los factores dominantes. Pasar de una estrategia solo DAM a un escenario DAM-RT casi duplicó los ingresos del primer año (+64%) y triplicó el IRR de los inversores (de 6.0% a 31.7%), reduciendo el payback de 10-12 años a 3-5. El CAPEX también resultó determinante: en el escenario optimista de NREL ($473/kW) los IRRs subieron a +15%, mientras que en el conservador ($844/kW) cayeron a <3%. Los parámetros técnicos como DoD y RTE tuvieron un impacto secundario, aunque importante: reducir DoD de 95% a 80% bajó ingresos un 16%, mientras que variar RTE entre 91% y 95% movió IRRs en menos de 1%.

Tabla A1. Resumen de análisis de sensibilidad para el nodo Pamplona

Scenario	Y1 Revenue ($m)	Project IRR (%)
Base Case (DAM, 93% RTE, 95% DoD, Mid CAPEX $756/kW)	8.9	4.9
DAM–RT Dispatch	14.7	16.1
Optimistic CAPEX ($473/kW)	8.9	15.5
Conservative CAPEX ($844/kW)	8.9	2.7
1 Cycle/Day	7.1	3.8
80% DoD	7.5	3.8
65% DoD	6.1	2.7
95% RTE	9.1	5.4
91% RTE	8.7	4.5

Desde una perspectiva práctica, este modelo ya ha aportado valor a Solea Power Corp., al servir como herramienta de filtrado preliminar para priorizar nodos antes de encargar estudios de interconexión con un alto coste asociado (Screening Study y Full Interconnection

Study). Al reducir tiempos y costes, el modelo permitió conservar recursos, acelerar decisiones y responder a las expectativas de stakeholders que buscan alta rentabilidad con bajo capital inicial. Para una startup compitiendo contra empresas con mayor respaldo, esta eficiencia representa una ventaja decisiva.

En conclusión, este trabajo demuestra que el almacenamiento en ERCOT representa tanto una oportunidad como un reto. Las oportunidades se maximizan cuando los proyectos están bien ubicados, se benefician de estrategias predictivas de despacho y de reducciones en CAPEX. Los riesgos derivan de la saturación en mercados de servicios complementarios, la incertidumbre regulatoria y la degradación tecnológica. El modelo aquí desarrollado, al combinar rigor técnico con realismo financiero y facilidad de uso, no solo contribuye académicamente, sino que también proporciona a la industria una herramienta práctica de apoyo a decisiones. Futuras extensiones del modelo deberían integrar despacho en tiempo real, modelado probabilístico de Monte Carlo y algoritmos de predicción de precios nodales basados en IA. En última instancia, este trabajo muestra que los BESS, correctamente modelados y desplegados, pueden pasar de ser activos dependientes del mercado a convertirse en pilares de rentabilidad para inversores y de resiliencia para la red de ERCOT.

OPTIMIZATION OF BESS PROJECTS & DISPATCH STRATEGIES IN THE ERCOT MARKET

Author: Fernandez de la Concha Rebollo, Iñigo
Director: Sangroniz Ojer, Iñigo
Collaborating Entity: Solea Power Corp. SA

ABSTRACT

Battery Energy Storage Systems (BESS) are rapidly emerging as cornerstone technologies for modern power systems, especially in markets with high renewable penetration and extreme price volatility. Nowhere is this more evident than in the Electric Reliability Council of Texas (ERCOT), which operates one of the world's most dynamic and unique electricity markets. ERCOT is an energy-only system without a centralized capacity market and with minimal interconnection to neighboring grids. This design amplifies the role of price signals in balancing supply and demand, resulting in high volatility, frequent curtailment of renewable output, and exposure to extreme events such as the 2021 winter storm. In this context, BESS offer a dual benefit: providing investors with opportunities for energy arbitrage and grid services while supporting ERCOT's resilience by absorbing surplus renewable generation and supplying peak demand. For developers like Solea Power Corp., a Houston-based startup expanding from solar into storage, these opportunities are tempered by high uncertainty and the prohibitive cost of early-stage studies. This thesis was motivated by the industrial need to create a robust, resource-efficient techno-economic model that can evaluate BESS feasibility at ERCOT's nodal level and guide investment decisions before committing resources to full interconnection studies.

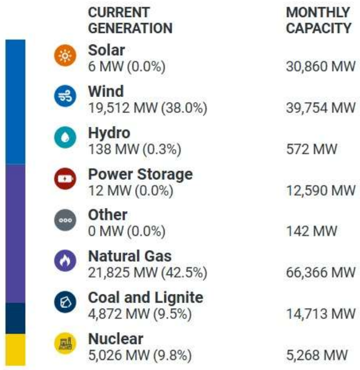


Figure A2. Fuel mix ERCOT market

The objective of this work is to design and apply a techno-economic modeling framework capable of simulating the performance and profitability of a 2-hour lithium-ion BESS across ERCOT's 17,000+ pricing nodes. Specifically, the model integrates three core dimensions:

I. Technical assumptions such as depth of discharge (DoD), state of charge (SoC), round-trip efficiency (RTE), and annual degradation.
II. Dispatch logic based on Day-Ahead Market (DAM) price spreads, with extensions to Day-Ahead/Real-Time (DAM–RT) hybrid strategies.
III. A project finance layer that includes capital expenditure (CAPEX), operating expenditure (OPEX), 30% standalone storage Investment Tax Credit (ITC), accelerated MACRS depreciation, and debt–equity structuring.

A parallel curtailment model was also developed to evaluate the added value of solar + storage co-location, particularly in regions such as West Texas where curtailment levels are high. Together, these components form a scalable and investor-grade decision-support tool for storage development.

The model was implemented through a hybrid data and simulation architecture. ERCOT's DAM price dataset, comprising over 3.9 million hourly nodal values between March 2021 and September 2024, was structured into a SQL database to enable efficient querying. Python acted as the intermediary, retrieving node-level prices and feeding them into an Excel/VBA dispatch engine where daily charge–discharge cycles were simulated under seasonal assumptions (1 cycle/day in summer, 2 cycles/day in winter). Degradation was applied externally to maintain modularity. The financial layer was embedded directly in Excel, ensuring accessibility for non-technical users. This SQL–Python–Excel pipeline reduced simulation runtime from over 5 minutes per node to under one minute, enabling full ERCOT benchmarking while remaining transparent and user-friendly.

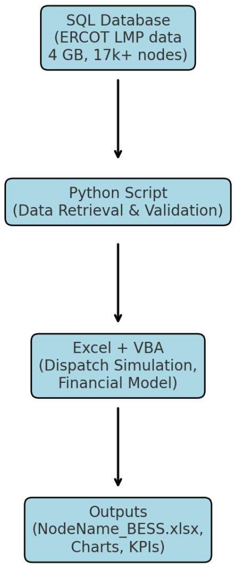


Figure A2. Workflow architecture of BESS techno-economic model

The results section first applied the model to two case studies: Pamplona (Houston Hub) and Santa Monica (North Hub). Pamplona benefited from high volatility and spreads, yielding Year 1 revenues of $89,412 per MW installation and project IRRs of 4.9% (unlevered) and 6.0% (levered). Santa Monica, by contrast, delivered lower revenues, $85,247 per MW, and weaker returns (3.9% for both IRRs), reflecting thinner spreads despite competitive solar pricing. These case studies highlight the necessity of nodal-level analysis, as hub averages alone obscure meaningful differences in profitability.

Expanding to the hub scale, results showed the West Hub leading with $90,497/MW-year, driven by volatility but constrained by curtailment and congestion. Houston followed at $87,505/MW-year, attractive for arbitrage but challenged by land and interconnection bottlenecks. North and South hubs underperformed in absolute terms but offered either stability (North) or strong co-location value (South). These findings underscore the decisive influence of location in ERCOT's BESS market.

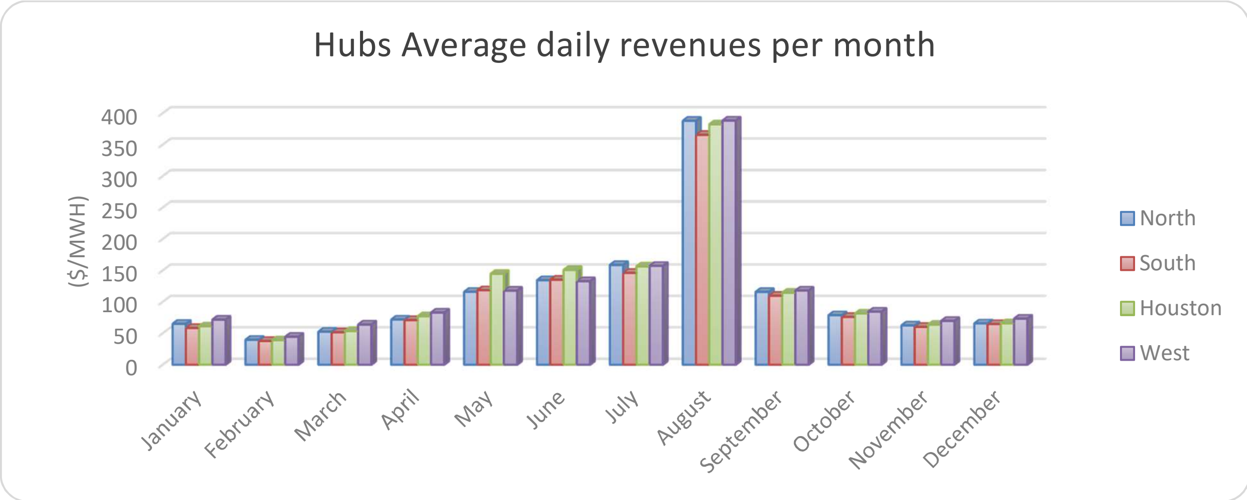


Figure A3. Average annual revenues across ERCOT Main Hubs, excluding Coastal and Panhandle

The sensitivity analysis revealed dispatch strategy and capital costs as the dominant levers of feasibility. Transitioning from a DAM-only strategy to an idealized DAM-RT scenario nearly doubled Year 1 revenues (+64%) and tripled shareholder IRR (from 6.0% to 31.7%), cutting payback from 10-12 years to 3-5. CAPEX proved equally decisive: under NREL's optimistic trajectory ($473/kW), IRRs rose to +15%, while conservative assumptions ($844/kW) reduced returns to <3%, close to unviability. Technical parameters such as DoD and RTE acted as secondary refinements, though still very important: lowering DoD from 95% to 80% cut revenues by 16% approximately, while adjusting RTE between 91% and 95% shifted IRRs by less than 1%. These results confirm that while technical optimization enhances margins, structural factors such as cost reductions and real-time trading strategies define project viability.

Table A1. Sensitivity Analysis summary table

Scenario	Y1 Revenue ($m)	Project IRR (%)
Base Case (DAM, 93% RTE, 95% DoD, Mid CAPEX $756/kW)	8.9	4.9
DAM–RT Dispatch	14.7	16.1
Optimistic CAPEX ($473/kW)	8.9	15.5
Conservative CAPEX ($844/kW)	8.9	2.7
1 Cycle/Day	7.1	3.8
80% DoD	7.5	3.8
65% DoD	6.1	2.7
95% RTE	9.1	5.4
91% RTE	8.7	4.5

From a practical perspective, this model has already delivered value to Solea Power Corp. by serving as a low-cost screening tool to prioritize nodes before commissioning costly interconnection studies. These studies, which include Screening Studies and Full Interconnection Studies, represent significant expenses in both time and consultant fees. By filtering nodes upfront, the model enabled Solea to conserve resources, accelerate decision-making, and align with the expectations of stakeholders seeking high-return, low-investment opportunities. For a startup competing against larger firms with deeper pockets, this efficiency represents a decisive advantage.

In conclusion, this thesis demonstrates that battery storage in ERCOT is both an opportunity and a challenge. Opportunities are greatest when projects are strategically sited, leverage predictive dispatch, and benefit from declining capital costs. Risks stem from market saturation in ancillary services, policy uncertainties, and degradation dynamics, all of which require careful modeling. The model developed here, by combining technical rigor with financial realism and operational usability, not only advances academic understanding but also equips industry practitioners with a practical decision-support tool. Future extensions could include real-time dispatch integration, probabilistic Monte Carlo modeling, and AI-based forecasting of nodal prices. Ultimately, this thesis shows that BESS, when properly modeled and deployed, can evolve from market dependent assets into cornerstones of both investor profitability and ERCOT grid resilience.

Table of Contents of the Report

List of Figures

List of Tables

ACRONYM'S LIST

ERCOT – Electric Reliability Council of Texas

ISO – Independent System Operator

DAM – Day Ahead Market

RTM – Real Time Market

BESS – Battery Energy Storage Systems

LMP – Locational Marginal Price

IEA – International Energy Agency

HVAC – Heating, Ventilation, and Air Conditioning

OMIE – Operador del Mercado Ibérico de Energía (Iberian Day-Ahead Market Operator)

CAPEX – Capital Expenditure

OPEX – Operational Expenditure

IRR – Internal Rate of Return

AS – Ancillary Services

FRRS – Fast Response Reserve Service

CRR – Congestion Revenue Rights

QSE – Qualified Scheduling Entity

PPA – Power Purchase Agreement

RUC – Reliability Unit Commitment

ECRS – ERCOT Contingency Reserve Service

ITC – Investment Tax Credit

IRA – Inflation Reduction Act

LDES – Long Duration Energy Storage

BMS – Battery Management System

SCADA – Supervisory Control and Data Acquisition

PCS – Power Conversion System

PV – Photovoltaic

EMS – Energy Management System

HVC – High Voltage Customer

FEMA – Federal Emergency Management Agency

SEI – Solid Electrolyte Interphase

SoC – State of Charge

Mid-SoC – Mid-State of Charge

DoD – Depth of Discharge

FCE – Full Cycle Equivalent

RTE – Round-Trip Efficiency

SoH – State of Health

LCOS – Levelized Cost of Storage

RRS – Responsive Reserve Service

FFR – Fast Frequency Response

PFR – Primary Frequency Response

PTC – Production Tax Credit

AI – Artificial Intelligence

ML – Machine Learning

SQL – Structured Query Language

SSMS – SQL Server Management Studio

CSV – Comma-Separated Values

API – Application Programming Interface

VBA – Visual Basic for Applications

KPI – Key Performance Indicator

NREL – National Renewable Energy Laboratory

SPV – Special Purpose Vehicle

LLC – Limited Liability Company

MACRS – Modified Accelerated Cost Recovery System

EBIT – Earnings Before Interest and Taxes

DSRA – Debt Service Reserve Account

MRA – Major Maintenance Reserve Account

NPV – Net Present Value

WACC – Weighted Average Cost of Capital

BOS – Balance of System

EPE – Electric Power Engineers

SPP – Settlement Point Price

EPC – Engineering, Procurement and Construction

DOCUMENT 1. PROJECT REPORT

1. INTRODUCTION AND PROJECT APPROACH

1.1 BACKGROUND AND CONTEXT

The Electric Reliability Council of Texas (ERCOT) manages the electricity grid for around 26 million people, covering approximately 90% of the state's total electricity demand. As an independent system operator (ISO), ERCOT is responsible for maintaining grid reliability and operating a unique energy-only market. In this system, power generators are paid only for the electricity they produce and sell, rather than receiving additional payments for simply being available, which is included in the ancillary services market working in parallel to the day-ahead and real-time markets. This structure makes ERCOT's market more dependent on price fluctuations to encourage supply, especially during periods of high demand or grid stress.

Over the past decade, Texas has experienced a rapid expansion in renewable energy capacity, primarily in wind and solar. By early 2025, according to ERCOT, installed wind capacity has almost reached 40 GW, while solar capacity has surged past 30 GW, with projections indicating continuous growth. This rapid influx of intermittent renewable generation has introduced significant challenges related to energy price volatility, particularly in the Day-Ahead Market (DAM) and the Real-Time Market (RTM). HVAC

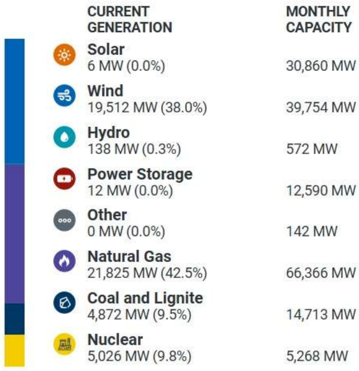


Figure 3. Fuel mix ERCOT market

ERCOT's operational structure differs notably from other U.S. electricity markets due to its energy-only market design and limited interconnection to external grids. This means that ERCOT does not rely on capacity payments to ensure generation adequacy; instead, it uses real-time price signals to incentivize both supply and demand behavior. The market operates primarily through three core mechanisms: the Day-Ahead Market (DAM), the Real-Time Market (RTM), and the Ancillary Services markets. In the DAM, market participants submit bids and offers for electricity supply and demand on an hourly basis for the next day, very similar to OMIE's day ahead market in the Iberian Peninsula. Accepted bids set binding schedules and prices, offering price certainty and early visibility into system conditions. The RTM, by contrast, settles imbalances between DAM schedules and actual real-time conditions through 5-minute price intervals (publishes in 15-minute price intervals in ERCOT's official website), capturing short-term fluctuations in demand and generation. These fluctuations are often driven by factors such as renewable output variability, forced outages, and load forecast errors, with a significant % coming from forced outages due to several external reasons, such as the malfunction of equipment due to severe meteorological conditions, something especially common in the southeast region, around Houston.

To maintain grid stability, ERCOT also procures ancillary services. There are 5 main ancillary services, which BESS (Battery Energy Storage Systems) assets are increasingly well-positioned to provide thanks to their fast response capabilities. These services are Regulation Up, Regulation Down, Responsive Reserve, Non-Spin Reserve, and the 2023 newly added Contingency Reserve, acting as an emergency buffer of the rest of reserves. Particularly, the latter has been very relevant to large proportion of battery reserves recently, something that will be discussed in later topics.

These 3 mechanisms are co-optimized within the broader market and cleared based on both price and system needs. Importantly, the lack of interconnection to other markets means ERCOT must always manage supply and demand balance internally, leading to higher levels of price volatility than in other ISOs. This market structure creates favorable conditions for BESS operators to pursue energy arbitrage strategies and capture high-value revenue streams from ancillary services. By maintaining available capacity for frequency regulation, BESS units can participate in grid stability services, while also charging during low-price periods, typically driven by renewable generation surpluses, and discharging during high-price intervals, such as during peak demand or supply shortfalls.

Price spreads between specific hours in a day in DAM and RTM, as well as the differences between DAM and RTM themselves, have widened due to increased renewable penetration, with instances of negative pricing during periods of excess supply and price spikes during peak demand. For example, in 2023, ERCOT recorded multiple instances of extreme price fluctuations exceeding $5,000/MWh due to supply-demand imbalances exacerbated by extreme weather events. These fluctuations have been seen in the past as well, so there's validity to believe it will continue occurring in the upcoming years.

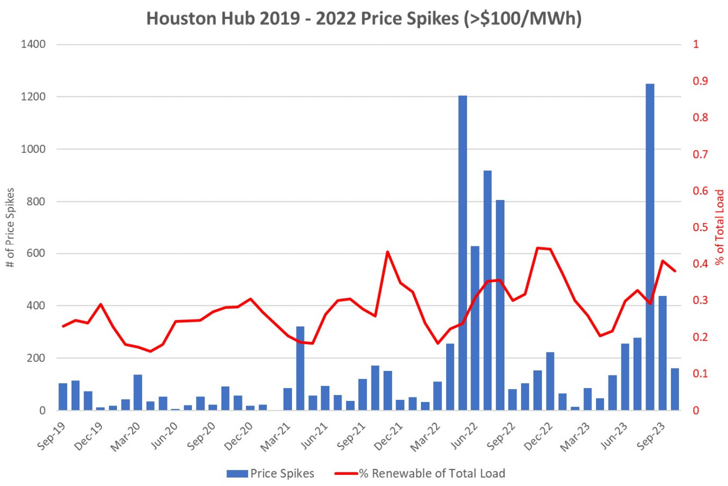


Figure 4. Price spikes in Houston Hub 2019-2022

To address these challenges, BESS have emerged as a critical technology to provide grid stability, optimize market participation, and enhance revenue streams for energy traders and project developers. BESS can store energy when prices are low and discharge when prices peak, capitalizing on arbitrage opportunities while improving grid resiliency. In addition, BESS also can capitalize as co-located installations to solar or wind farms, capitalizing on curtailment periods of high renewable energy generation with negative market prices, by storing the renewable energy and selling it at a higher price at a later time.

1.2 MOTIVATION

The increasing economic viability of battery storage projects has created a compelling case for expanding beyond standalone solar developments into hybrid solar-plus-storage systems. At Solea Power Corp, my primary role has been to drive this expansion by integrating BESS into our project pipeline, capitalizing on the growing investor interest in energy storage solutions.

This transition aligns with the broader market trend where energy developers seek to maximize returns by leveraging price arbitrage opportunities and ancillary service revenues in the ERCOT market. As price volatility intensifies due to renewable penetration, the ability to store and dispatch energy at optimal times has become a critical factor in project success.

Beyond financial incentives, the implementation of BESS contributes to grid stability by mitigating extreme price fluctuations and alleviating supply-demand imbalances. By reducing curtailment of renewable energy and optimizing dispatch strategies, storage solutions play a crucial role in enhancing market efficiency. This project not only supports Solea's strategic objectives but also aligns with broader industry efforts to accelerate the energy transition, positioning battery storage as a cornerstone of future electricity markets.

Having seen recent needs of grid stability on an international scope, the use of BESS is in its peak momentum to ensure a correct energy transition, as it's seen that a massive amount of intermittent renewable energy output across the day doesn't completely replace fossil fuels unless energy storage can control when to inject this energy into the grid or not.

On a personal and professional development level, this thesis also seeks to reflect the extensive work behind the modeling and market research efforts, with the goal of helping expand Solea Power Corp.'s project scope by opening a new line of business focused on BESS development and identifying new revenue opportunities

1.3 PROJECT OBJECTIVES

The aim of this study is to develop a techno-economic model for optimizing BESS deployment within ERCOT. The model is based on DAM price data from March 2021 to September 2024, analyzing historical trends across more than 17,000 pricing nodes in the ERCOT network. By simulating the operation of a 2-hour lithium-ion battery facility, the model evaluates revenue generation potential under varying market conditions. Key parameters include:

- Charging during the two consecutive cheapest hours per day
- Discharging during the two most expensive hours per day
- Considering seasonal variations in charge-discharge cycles (1 or 1.5 cycles/day)
- Incorporating degradation factors and financial considerations (CAPEX, OPEX, tax incentives, and financing structure)

In turn, this thesis aims to enhance the development and deployment of BESS within the ERCOT market by leveraging advanced techno-economic modeling and optimized dispatch strategies. The primary objectives of the project are outlined below:

Optimize BESS dispatch strategies for profit maximization

The project seeks to develop and refine dispatch strategies that maximize the profitability of BESS installations in ERCOT. By simulating historical Day-Ahead market data, the model identifies optimal charge and discharge windows, charging during periods of low prices and discharging when prices peak. This approach is intended to improve financial returns while promoting efficient operational planning.

Deliver a scalable model for BESS across ERCOT's 17,000+ nodes, identifying biggest opportunities

A core component of this project is the development of a flexible techno-economic model designed to assess the feasibility of BESS deployment across ERCOT's expansive nodal network. By integrating location-specific price dynamics, including specific locational marginal prices (LMPs) across the nodes and infrastructure characteristics, the model enables developers and investors to identify high-return sites and evaluate the trade-offs between standalone and co-located configurations with renewable assets. To put into business context, if a landowner is willing to sell/rent their land, this model could analyze the land's projection of revenues for the next 15 years and analyze that specific location's financial metrics, such as project IRR.

Assess the Technological Viability of Utility-Scale Lithium-Ion Batteries

A key goal is to evaluate the technical and economic suitability of lithium-ion batteries for utility-scale storage applications. The analysis focuses on configurations such as 1-hour, 2-hour, and 4-hour batteries, deep diving into 2-hour batteries for this thesis, considering round-trip efficiency, degradation profiles, and lifecycle performance. This objective ensures that the system design is aligned with realistic operational and investment horizons.

Evaluate the Impact of Market Price Volatility on BESS Performance

To address market uncertainties, the project analyzes the sensitivity of BESS revenues to price fluctuations over multi-year periods. By modeling exposure to volatility in both the DAM and RTM, this objective assesses potential financial risks and informs more resilient investment decisions.

Support Renewable Integration by Enhancing Market Stability

The thesis explores how strategically deployed BESS can contribute to greater grid reliability and price stability amid increasing renewable penetration. By absorbing excess generation and releasing stored energy during supply deficits, batteries can reduce price spikes and curtailment, ultimately supporting broader decarbonization efforts.

2. STATE OF THE ART: ERCOT MARKET AND BATTERY STORAGE TECHNOLOGIES

2.1 ERCOT MARKET OPERATIONS

The ERCOT grid operates a nodal system independently from the Eastern and Western interconnections, making it a unique and self-contained power market in the United States. With over 17,000 pricing nodes, ERCOT relies on locational marginal pricing (LMP) to reflect real-time supply and demand conditions at each node. This structure promotes geographically optimized development, as generators, and increasingly battery storage systems, are incentivized to locate in areas with high price volatility or congestion. Within this framework, short-term electricity trading takes place across two primary markets: the Day-Ahead Market (DAM), where participants can hedge against price fluctuations by scheduling energy deliveries a day in advance; and the Real-Time Market (RTM), which settles every five minutes based on actual system conditions. Both markets are supported by the Ancillary Services Market, which ensures system stability through frequency regulation, spinning reserves, and fast-response products like the FRRS (Fast Response Reserve Service).

In addition to these short-term markets, ERCOT also supports longer-term mechanisms such as the Congestion Revenue Rights (CRR) Auction and bilateral trading, where Qualified Scheduling Entities (QSEs) engage in contracts ranging from monthly to multi-year durations. One common form of long-term agreement is the Power Purchase Agreement (PPA), a contract between a generator and an QSE that locks in energy prices over time to shield both parties from short-term market volatility. While ERCOT does not operate a traditional capacity market like those found in the UK or Iberian Peninsula, it does maintain a Reliability Unit Commitment (RUC) mechanism to ensure adequate generation is available during periods of tight supply. As a result, strategic coordination between ERCOT and market participants is essential to maintain both system reliability and economic efficiency. The following figure illustrates how the ERCOT electricity market is structured across timeframes.

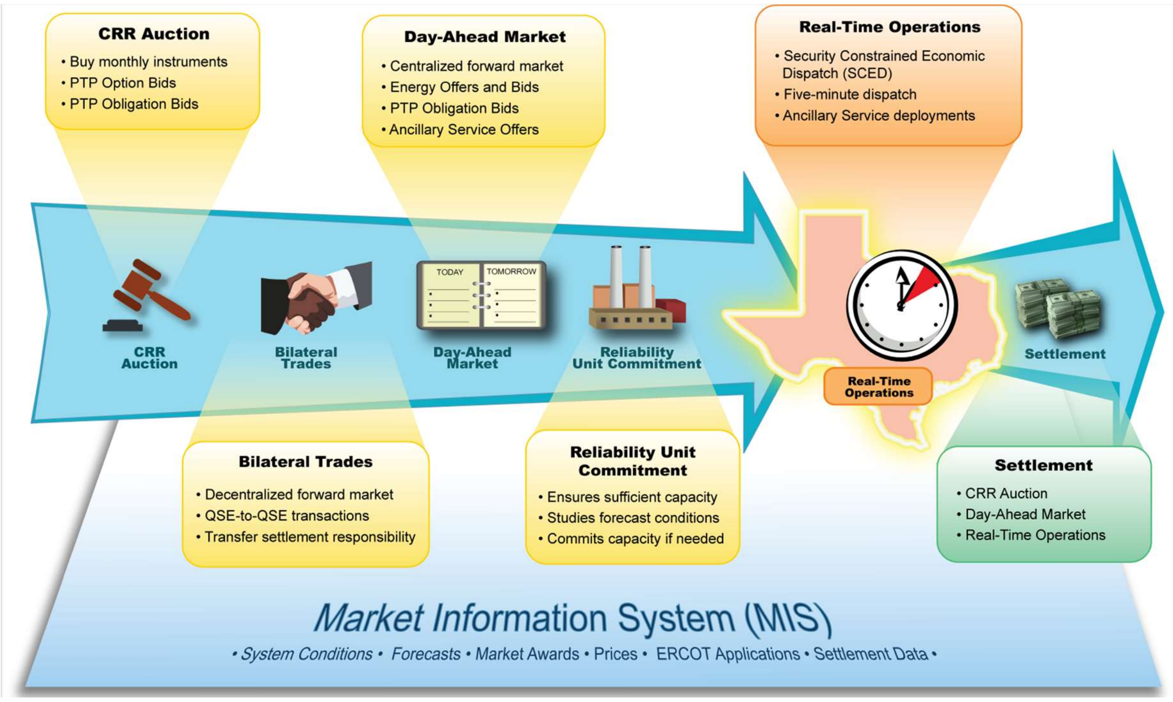


Figure 5. Market Information System Summary (ERCOT)

Out of this whole market, BESS gains a significant role in the short-term markets, where volatility comes in to play and BESS could act as a solution to decrease this effect. The Day-Ahead Market (DAM) allows generators and storage operators to lock in prices a day in advance based on forecasted demand and supply conditions. BESS can leverage DAM participation to optimize dispatch schedules, commit capacity, and hedge against volatility in the Real-Time Market, although DAM also experiences high levels of volatility, especially in extreme weather events. In contrast, the Real-Time Market (RTM) clears every five minutes and reflects the most immediate supply-demand imbalances. This is where the highest volatility can occur, paired with the high risk of trading in this market. This market volatility is translated sometimes into hundreds or even thousands of dollars per MWh of difference in a single day, difference that can be capitalized by BESS facilities if modeled properly.

The Ancillary Services Market provides payments for maintaining system reliability through the 5 ancillary services markets there are: Regulation Up, Regulation Down, Responsive Reserve, Non-Spin Reserve and the ERCOT Contingency Reserve Service (ECRS), which recently came into play as of June 2023. Offers on ancillary services are submitted in a MW basis and are paid in $ / MW. According to ModoEnergy, from January to June 2023, 87% of BESS revenues in ERCOT came from ancillary services, signaling a clear opportunity for BESS to make consistent revenues at that time.

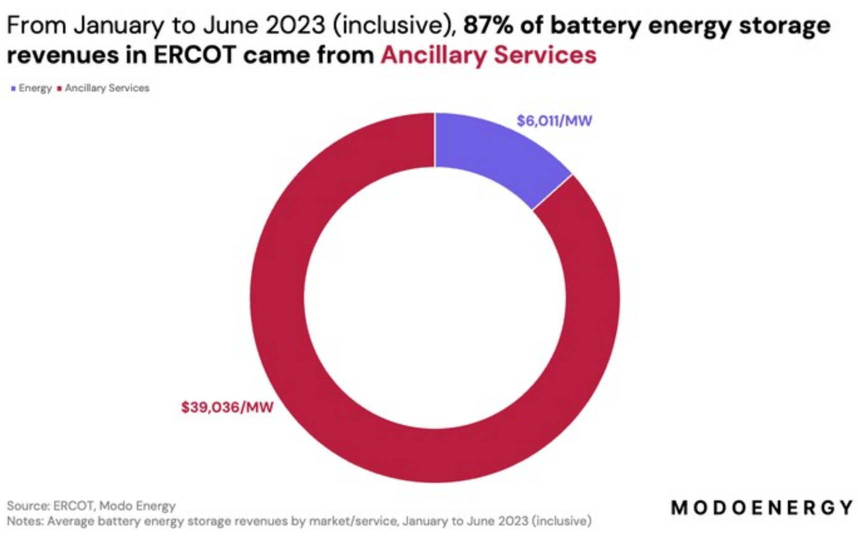


Figure 6. BESS revenue breakdown in 2023's first semester (ModoEnergy, 2023)

The integration of renewable energy has transformed Texas's electricity landscape, with wind and solar generation now accounting for more than 40% of total generation (U.S. Energy Information Administration [EIA], 2024), a share expected to continue growing steadily in the coming years. This shift, however, has introduced even more volatility into the market, with frequent occurrences of negative pricing (curtailment) when renewable generation outstrips demand, and extreme price spikes during peak consumption periods. The widening spread between DAM hourly prices in the same day has heightened the importance of energy storage solutions, as they offer a means of mitigating these fluctuations while enhancing system reliability. One of the defining features of ERCOT as already mentioned is its nodal pricing system, which contains over 17,000 unique LMPs across the grid. This granular pricing mechanism reflects local congestion, losses, and supply-demand mismatches in real time, and introduces both risk and opportunity for battery operators. Strategically sited BESS assets can capitalize on locational price volatility, charging when local prices dip due to excess solar or wind generation, and discharging when congestion spikes prices at nearby nodes, especially during evening hours where no renewable energy generation is present, and people get back from work. This makes site selection and nodal modeling especially important for standalone storage developers seeking to maximize revenue.

As of 2025, ERCOT has over 90GW of battery storage projects in its interconnection queue, reflecting the growing interest in storage as a solution to market inefficiencies. However, it has to be pointed out that this large queue doesn't reflect reality as of now, as less than 30% of BESS projects in the queue actually get to the construction phase, highlighting the fierce competition and still lack of full knowledge on when and where to build a project. This growth has been further stimulated by regulatory incentives, particularly the extension of the 30% Investment Tax Credit (ITC) for standalone storage projects under the Inflation Reduction Act (IRA), which, although a controversial theme as of now, will keep being available until 2032.

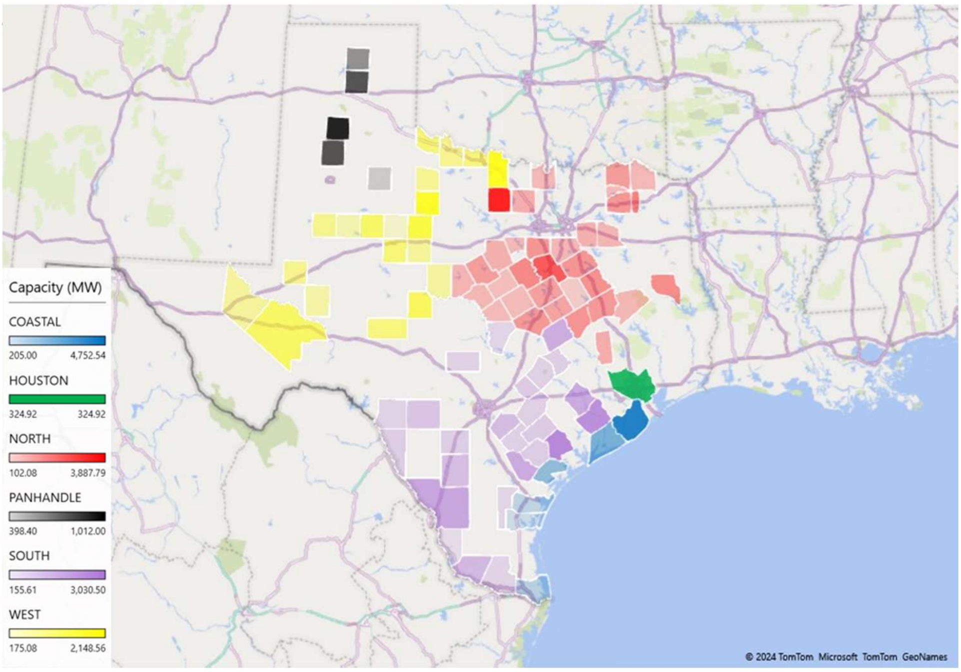


Figure 7. ERCOT's BESS interconnection queue by location and capacity

A well-known example of market volatility in ERCOT came in the winter storm in February 2021, which led to prolonged outages and extreme price spikes across Texas. This event highlighted the vulnerability of thermal generation and the importance of dispatchable energy reserves. Similarly, daily solar oversupply in regions like West Texas now causes frequent midday price drops, followed by sharp ramps during evening demand peaks, ideal conditions for two-hour lithium-ion systems to perform arbitrage. According to an expert interview conducted from a local engineering company, "During that storm, we almost paid for all our BESS' projects CAPEX through energy arbitrage, as prices spiked enormously." To back this claim, the EIA published, "In February 2021, wholesale prices held at or near the $9,000/MWh ERCOT price cap for approximately 77 hours, from midnight on February 15 to the morning of February 19." This ultimately shows that volatility can happen at any given time, and both BESS and the grid can benefit economically from a profound BESS integration, bearing in mind this was a very uncommon occurrence, although with increased probability in recent times as observed in recent years, where the occurrence of extreme weather events has increased significantly.

In addition, while these seasonal patterns have remained relatively stable in recent years, long-term climate projections for Texas suggest potential shifts that could alter electricity demand peaks and renewable generation profiles. Average summer temperatures are expected to rise, increasing cooling loads and potentially extending the duration of daily price spikes into late evenings. Conversely, more variable winter weather, including extreme cold storms similar to the 2021 case, could create additional intraday peaks beyond the current two-cycle winter profile. Such changes, driven by both climate change and evolving consumption behavior, may influence the optimal seasonal dispatch strategies for BESS in the future. As a result, models that hard-code seasonal cycles based solely on historical data should be periodically revisited to ensure alignment with emerging climatic and market conditions.

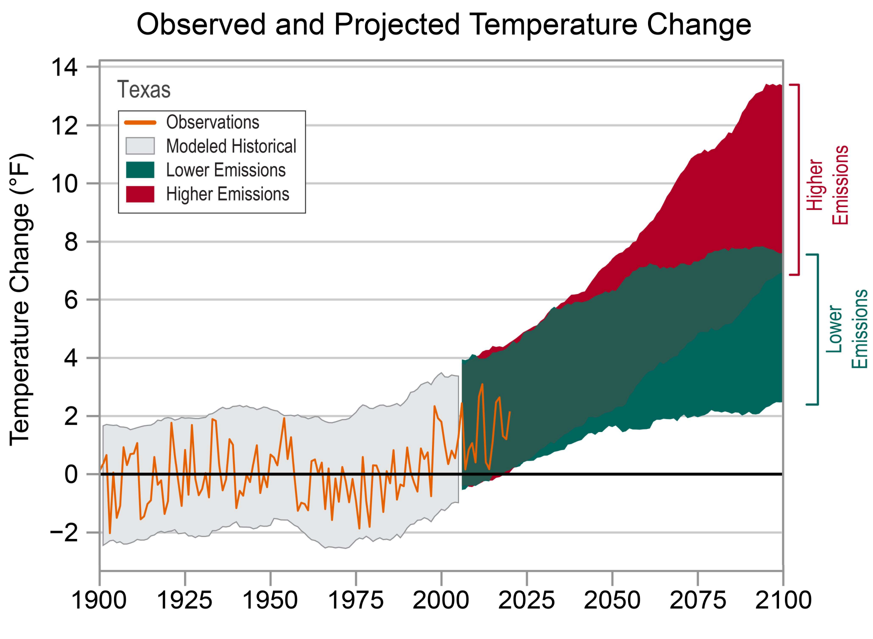


Figure 8. Projected temperature increases in different emissions scenarios in Texas (North Carolina Institute for Climate Studies, 2022)

2.2 UTILITY-SCALE BATTERY ENERGY STORAGE TECHNOLOGIES

BESS have emerged as a fundamental component of modern grid infrastructure, driven by rapid technological advancements and cost reductions. The global energy storage market has experienced unprecedented growth. According to IEA, "Storage installations in 2024 beat expectations with 205GWh installed globally, a staggering y-o-y increase of 53%. The grid market has once again been the driver of growth, with more than 160GWh deployed globally, of which 98% was lithium-ion." In the United States, the sector is expanding at an annual growth rate exceeding 30%, with ERCOT at the forefront of this transition due to its dynamic pricing structure and increasing reliance on renewable energy sources.

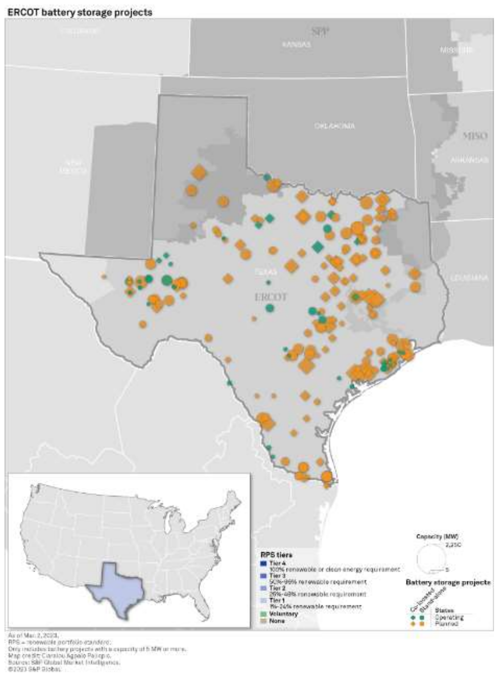


Figure 9. Standalone and co-located BESS facilities in ERCOT market

Now, how does a battery energy storage system work exactly? Battery energy storage systems (BESS) are electrochemical technologies that allow energy to be stored and discharged later, playing a key role in enhancing grid flexibility and reliability. These systems can charge from the grid or directly from generation assets, like solar installations, and later release stored energy to supply electricity or provide ancillary services during periods of high demand or reduced supply. Various battery chemistries exist for grid-scale applications, including lithium-ion, lead-acid, redox flow, and molten salt technologies, each with distinct performance characteristics and trade-offs. Among them, lithium-ion batteries currently dominate the utility-scale market in the United States and globally, driven by rapid technological advancements and significant cost reductions.

Lithium-ion batteries are divided as of now into 4 types, each playing a completely different role in market operations, and having completely different levels of technology maturity: one-hour, two-hour, four-hour and eight-hour batteries. One-hour batteries primarily serve ancillary service markets, where rapid response times are crucial for frequency regulation. Two-hour batteries, which are the focus of this study, are particularly suited for energy arbitrage, capitalizing on the price differentials between low-price charging periods and high-price discharge periods, although it has been seen that many benefit from ancillary services regulation as well. Meanwhile, four-hour batteries are increasingly utilized for peak shaving and capacity firming, offering extended discharge durations to stabilize grid fluctuations, although its level of technological maturity and costs are still a short-term barrier for a clear entry. On the other hand, eight-hour BESS systems are gaining attraction on the market to possibly replace CCGT's as a long-term ancillary services response, but it's still being studied and on a pre-implementation phase.

2.2.1 System Architecture and Core Components

There are several crucial components for an optimal functioning of BESS systems. These are:

- Battery cells: This is the main storage component which can vary in type, including lithium-ion and lead-acid batteries, as well as several others discussed.
- Battery Management System (BMS): Serves as a SCADA (Supervisory Control and Data Acquisition) solely focused on monitoring battery health and functionality to ensure safe operations.
- Power Conversion System (PCS): Controls the bidirectional flow of power (charge and discharge cycles) and converts DC power from the battery to AC power at an appropriate voltage level required by the network, using an inverter and a set up transformer, similar components to a PV (Photovoltaic) installation. This is crucial to couple BESS to the electrical grid, so it can properly function.

- Energy Management System (EMS) and SCADA: Serve as the general SCADA and performance optimization component. These components work simultaneously together to optimize the performance and integration of BESS into the broader power system

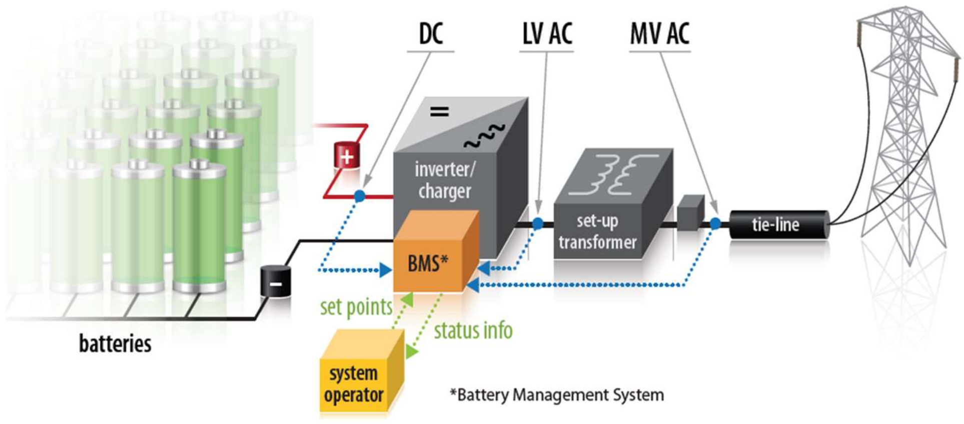


Figure 10. Key components of BESS interconnected at the transmission substation level (Denholm, 2019)

Once the key technical components are discussed, there are also auxiliary components that are necessary for the BESS system to function optimally to be mentioned. This equipment/infrastructure includes:

- Auxiliary Services Room: This subsystem is responsible for supplying low-voltage power to various auxiliary equipment throughout the BESS installation. This includes internal lighting, HVAC and cooling systems, the later integrated in the battery enclosure, control systems, and safety mechanisms such as fire detection. It ensures the continuous operation of non-power-conversion elements, especially during low-demand or stand-by periods. One of the key components in terms of energy consumption costs is included in this room, which is the HVAC and cooling systems, as they are expected to work all year round to maintain the batteries' optimal functional temperature.

- Storage Room: Also known as a warehouse. This room is designated for housing spare parts and essential equipment required for the preventive, predictive and corrective maintenance of the BESS. By keeping critical components on-site, operators can reduce system downtime in case of minor faults or failures. These critical components include spare battery modules (key component in OPEX, as several modules are replaced each year to maintain the BESS at peak power performance), replacement fuses and sensors, as well as specific tools for battery servicing used by on-site operators if needed.
- Control Room: This is the central node for the monitoring and management of the BESS. It hosts the SCADA systems, battery management platforms, and data acquisition servers that collect real-time system metrics and performance indicators. From this room, operators can visualize, control, and optimize system operation.
- Metering Cabinet: The metering cabinet is used to measure and transmit active and reactive power flows at the point of interconnection. It ensures compliance with market and grid operator requirements, such as those mandated by ERCOT, by providing accurate import/export data for billing, dispatch validation, and operational records.
- High Voltage Customer (HVC) Kiosk: This kiosk is a must for all energy systems functioning on the grid. It serves as a safety and isolation interface between the BESS facility and the utility grid. It enables operators to disconnect the system during planned maintenance or automatically during fault conditions. The HVC kiosk contains switchgear and circuit breakers designed to handle high voltage levels (typically 11kV to 33kV) used in grid interconnection.
- Battery Container: The battery container is the structural and functional unit that houses the core energy storage elements. Typically built from reinforced steel or shipping container shells, it is engineered for thermal management, safety, and modularity. Each container includes its own fire suppression system, local battery management units, and environmental controls. These fire suppression systems have been an ongoing work in progress due to the high toxicity of gases emitted in a BESS fire in Arizona, which raised the concern of the Federal Emergency Management

Agency (FEMA), which conducted R&D studies in the University of Texas at Austin to develop standard operating procedures in the case of a BESS fire.

2.2.2 Lithium-ion batteries

Lithium-ion batteries are electrochemical energy storage systems that store and release electrical energy through controlled chemical reactions, redox reactions to be specific. At their core, they consist of two electrodes, a negative electrode (called the anode) and a positive electrode (called the cathode), separated by an electrolyte and a porous separator. Two current collectors, positive and negative, finish up the initial setup of a lithium-ion battery. During operation, lithium ions (Li^{+}) shuttle back and forth between the two electrodes, which is what enables the battery to charge and discharge repeatedly.

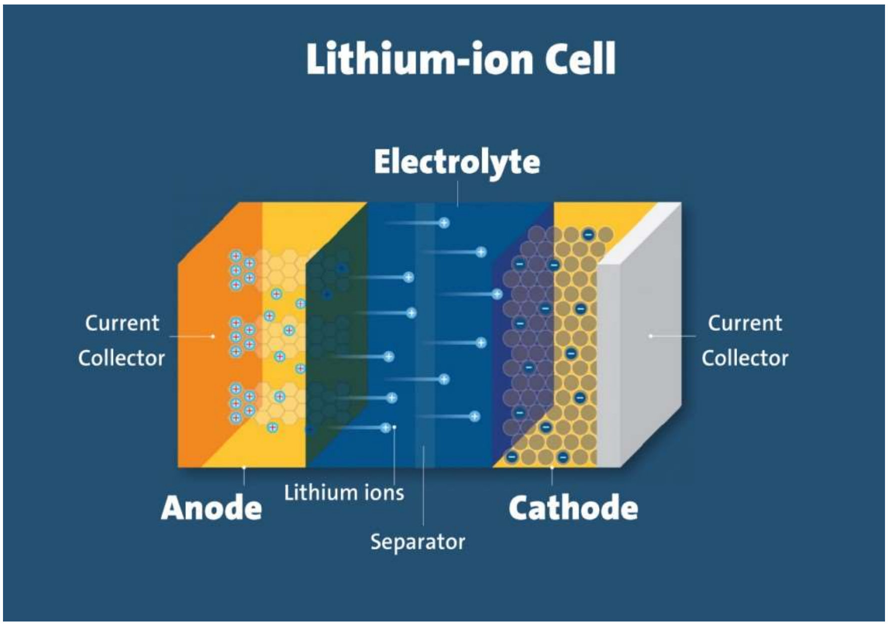


Figure 11. Lithium-ion cell composition (Source: Octopart)

When the battery is charging, an external electrical current is applied, which forces lithium ions to leave the cathode and move through the electrolyte toward the anode. At the same time, electrons travel through the external circuit (since they cannot pass through the electrolyte) and reach the anode, where they combine with the lithium ions. These ions are then stored in the anode's material structure, commonly made of graphite, through a process called intercalation. In this state, the battery is storing energy in chemical form. During discharge, the process is reversed. Lithium ions leave the anode and migrate back through the electrolyte toward the cathode, releasing energy in the process. As they move, electrons flow again through the external circuit to power a load (such as the grid), meeting the lithium ions at the cathode where they are reabsorbed into its structure, often made from lithium metal oxides like Lithium iron phosphate (LFP). This movement of ions inside the battery and electrons through the external circuit is what delivers electrical power to the system. The separator placed between the anode and cathode serves a critical safety role by physically preventing the electrodes from touching and causing a short circuit, while still allowing lithium ions to pass through. Meanwhile, the electrolyte, typically a solvent with lithium salt, facilitates ionic conductivity between electrodes without allowing electron flow internally.

These charging and discharging cycles are highly reversible under proper conditions, which is what allows lithium-ion batteries to be used for thousands of cycles. However, over time, side reactions such as solid electrolyte interphase (SEI) formation, lithium plating, or loss of active lithium can reduce the efficiency of ion movement and ultimately degrade the battery's performance and its State of Health, which will be discussed further along the document.

In the context of utility-scale battery energy storage systems, lithium-ion technology is implemented by combining thousands of individual cells into modules, racks, and containerized systems. These are then integrated with power electronics, thermal management, and control systems to form a grid-connected solution capable of charging from or discharging to the grid. Although the principle of operation remains the same as in consumer-scale batteries, the complexity increases significantly due to scale, safety, and thermal uniformity requirements.

Advantages

Lithium-ion batteries have become the preferred choice for utility-scale energy storage systems due to their combination of high performance, scalability, and commercial maturity. One of their most notable advantages is their high energy density, which allows a large amount of energy to be stored in a relatively small footprint, being a critical factor for grid-scale installations where land use may be constrained. To make a fair comparison, 1MW of solar occupies around 2.5-3 acres, whereas 100MW of a 2-hour lithium-ion BESS occupies around 5 acres, so roughly 50 times less space, hence a reduction in environmental impact. On top of their small footprint, their modular architecture allows flexibility in system sizing and deployment, from small commercial units to multi-megawatt grid-connected plants, meaning a BESS can be the exact size needed for a project without having to over dimension or under dimension the installation.

In addition, lithium-ion systems offer fast response times and high-power capabilities, enabling them to react within milliseconds to grid signals. This makes them ideal for applications such as frequency regulation, voltage support, and energy arbitrage in dynamic markets like ERCOT. Another key strength is their round-trip efficiency, typically ranging from 85% to 93%, which means that most of the energy stored can be recovered during discharge. Their ability to complete thousands of cycles before significant degradation also contributes to strong long-term performance. These advantages, combined with rapidly falling battery costs driven by EV-sector demand (refer to chapter 2.3), have positioned lithium-ion technology as the dominant solution in today's energy storage landscape.

Disadvantages

Despite their widespread adoption, lithium-ion batteries also present several technical and economic challenges, especially in long-duration or harsh operating environments. First, they are sensitive to extreme temperatures: high heat accelerates degradation exponentially and may lead to thermal runaway, while low temperatures increase internal resistance and reduce performance. This translates into needing complex thermal management systems, particularly in hot climates like Texas, adding to both OPEX and auxiliary consumption, meaning location is also an important factor when it comes to operational costs. Another limitation is their duration capacity; Lithium-ion batteries are typically optimized for 1 to 4 hours of discharge, which makes them less suitable for long-duration energy shifting or seasonal storage needs. However, there are optimistic advancements regarding 8-hour BESS, which is crucial in longer term ancillary services. Furthermore, these batteries require careful charge/discharge management to avoid deep cycling or overcharging, both of which accelerate degradation and reduce system life, acting as a barrier to overwork the battery as much as desired.

On the economic side, concerns remain around the availability and ethical sourcing of critical materials such as lithium, cobalt, and nickel, especially as global demand rises and these resources are scarce, especially lithium, which is the core component of the batteries. Safety is also a key issue: while modern systems include advanced Battery Management Systems (BMS), there is still an inherent risk of fire due to the flammable organic electrolyte used in most lithium-ion chemistries. "In April 2019, an unexpected explosion of batteries on fire in an Arizona energy storage facility injured eight firefighters." (FEMA, 2020)

2.2.3 Operational and Degradation Characteristics of Lithium-Ion Batteries

To develop an accurate techno-economic BESS model, it had to be understood what technicalities make a BESS function one way or another and find the optimal point to maximize revenue and useful life of battery modules in the installation. Technical specifications such as state of charge, depth of discharge, functioning temperature, and round-trip efficiency are not only essential for evaluating the performance of the system, but also critical for designing strategies that preserve long-term functionality and financial viability.

State of Charge (SoC)

State of Charge (SoC) refers to the percentage of a battery's total capacity currently stored and available for use. Maintaining a high SoC over extended periods, particularly above 80%, has been shown to accelerate calendar ageing due to increased chemical instability and higher rates of reactions. Conversely, persistently low SoC levels can result in reduced power availability and faster internal resistance buildup. To mitigate both forms of degradation, operational strategies typically define an optimal SoC window, often between 20% and 80%, within which the system cycles during regular operation. This practice helps to extend the usable life of the battery while maintaining adequate flexibility for energy dispatch. As an example of what this means in a practical case, if a battery is fully charged for 12 hours in a day and fully discharged for the remaining 12 hours (assuming ramp up charge and ramp up discharge time is negligible), the state of charge of the battery would be 50% on average, which is also called the mid-state of charge (Mid-SoC). To back this claim, the European Union funded a project named "Batteries 2020", which united nine battery experts to study the effect, along a few other effects, of SoC on battery ageing. Figure 12 shows the capacity of a battery at different SoC levels throughout its lifetime, in storage days.

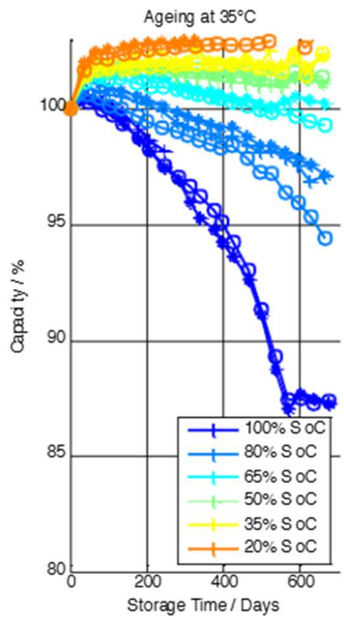


Figure 12. Capacity over battery cell lifetime at different SoC levels (Timmermans et al., 2016)

It can be observed that as SoC increases, the decrease in capacity over time is exponential, therefore the model has to carefully follow a path where the battery is not full for long periods of time, so that degradation doesn't become exponential.

Depth of Discharge (DoD)

DoD measures the portion of a battery's capacity that is discharged in a single cycle. The severity of DoD is a primary factor in cycle ageing, with deeper discharges inducing greater mechanical and chemical stress on battery materials. Lithium-ion cells exhibit significantly longer lifetimes when operated with shallower DoD; for instance, reducing DoD from 100% to 50% can nearly double the number of achievable full cycle equivalents (FCE). FCE are defined as number of complete cycles, from 100% of the energy rated capacity to 0%, without meaning it does that in one go, rather in a set of lower rated cycles to not overwork the battery. This correlation between DoD and number of FCE is due to the reduced strain on the electrode-electrolyte interfaces and lower thermal stress within the cell. As such, managing DoD is a key operational lever for maximizing lifetime energy throughput and should be taken into account when designing the model, as choosing between one DoD or another can make a project feasible or not. Figure 13 shows the capacity curves at different DoD levels for a battery working at 50% Mid SoC and 25ºC, which are criteria close to an optimal level of functioning.

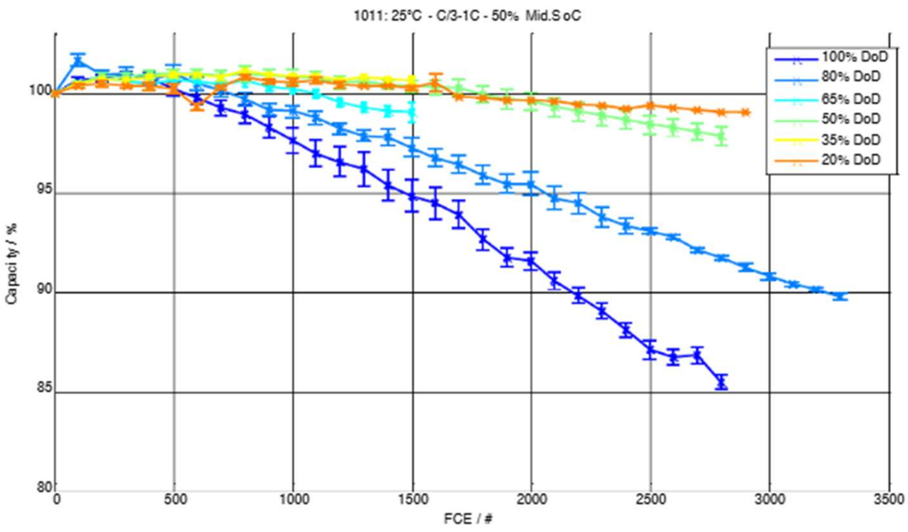


Figure 13. Capacity curves of battery cell at 25ºC and 50% Mid-SoC at different DoDs (Timmermans et al., 2016)

Following a similar trend as SoC, the higher the Depth of Discharge used in a BESS system, the more exponential the capacity degradation becomes. This has to be carefully considered for the model, as lower DoDs mean lower energy storage on average, hence less revenues, but higher DoDs means higher battery replacement costs, so an optimal DoD shall be picked for the model. To further acknowledge the importance of DoD in capacity degradation, Figure 14 shows 2D and 3D cell degradation models, which show the importance of not overloading a battery cell.

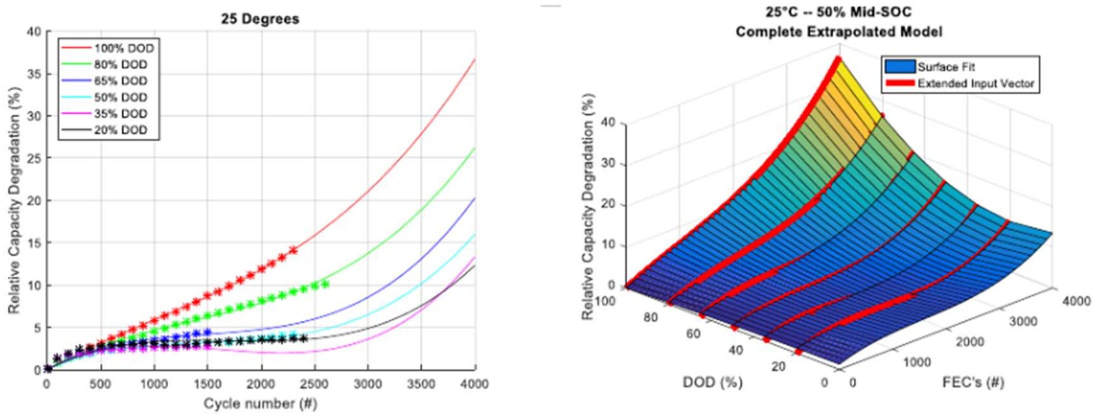


Figure 14. Capacity degradation curves at 25ºC and 50% Mid-SoC at different DoDs throughout the cell's lifecycle, measured in FCEs. The figure shows extrapolated 2D and 3D degradation models tested. (Timmermans et al., 2016)

Temperature

Temperature is also a key factor to be considered when ensuring optimal system performance. When temperatures are too low, typically below 15 °C, the internal resistance of the battery increases, which reduces power output and slows down the chemical reactions inside the cells. In addition, charging at low temperatures also raises the risk of lithium plating, a condition where lithium metal deposits on the anode instead of intercalating properly, potentially leading to faster degradation and even safety risks.

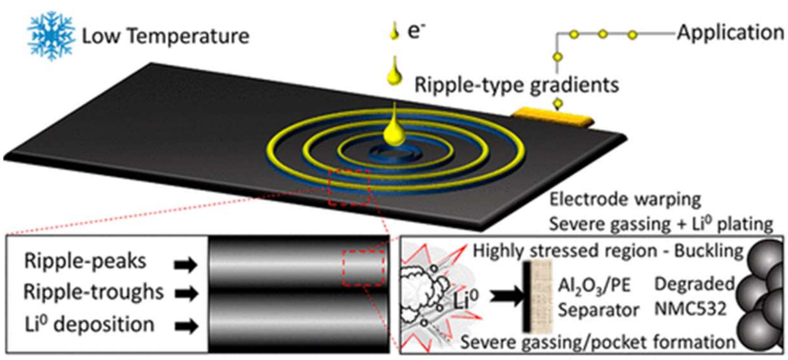


Figure 15. Example of lithium plating due to low temperatures (Liu et al., 2020)

On the other hand, high temperatures above 35–40 °C accelerate chemical ageing. This includes faster breakdown of the electrolyte, which in turn reduces the battery's capacity and efficiency. Long-term exposure to heat can also damage the battery's internal structure and raise impedance. As a result, most lithium-ion BESS installations are designed to operate within an ideal range of 20 °C to 30 °C. To stay within this range, utility-scale systems rely on active cooling and HVAC systems that manage container temperatures and help extend the life of the batteries, even when they are cycled intensively or exposed to extreme weather conditions. This HVAC system in locations like West Texas, known for long periods of dry heat, is key to ensure an optimal performance, and is also a large component of energy consumption in the installation. The following figure, from the Batteries 2020 study, shows the difference between battery ageing at different temperature levels, combined with SoC levels mentioned earlier.

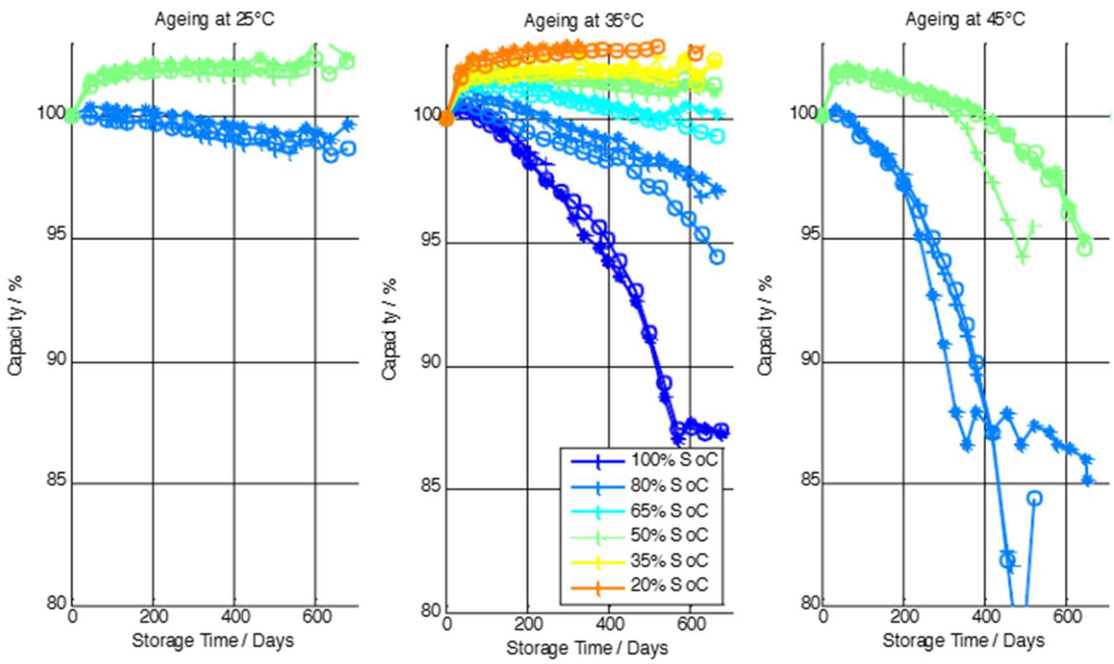


Figure 16. Capacity curves at different temperature levels and different SoC levels

It can be observed that ageing accelerates at higher temperature levels, backing up the importance of a constant battery container temperature of around 25ºC to maintain optimal BESS conditions. Not only that, but a correct and optimal combination of these 3 variables is crucial for battery operators to conserve batteries and maximize revenues throughout all the batteries' lifetime.

Round-Trip Efficiency (RTE)

RTE is defined as the ratio between the energy discharged by the battery and the energy initially used to charge it, taking into account it can be measured at different points of the installation (BESS to transformer, BESS to inverter terminals, etc.). For lithium-ion systems, measured at the inverter terminals, this efficiency typically ranges from 85% to 93% depending on technology, ambient conditions, and power conversion losses. RTE naturally declines over time because of internal resistance buildup and degradation of electrode materials, chemical reactions that can be accelerated depending on the 3 variables discussed earlier. Maintaining a high RTE is essential for ensuring that a significant portion of the energy cycled through the system can be monetized or delivered to the grid. RTE is essentially what can increment IRR within BESS projects, ultimately increasing the positive gradient movement of investors into these projects. Not only that, but as more projects go underway, demand will increase significantly, hence technology will develop and BESS projects will increasingly have better RTE's and lower costs, increasing even further investor movement. This metric will be discussed further down in the model as a key assumption to achieve accuracy in the model.

Capacity Fade and State of Health (SoH)

Capacity fade/degradation is a natural process that reduces the maximum charge a battery can hold over time. It is influenced by two main degradation pathways: calendar ageing and cycle ageing.

Equation 1. Total capacity degradation as a sum of the two degradation pathways (Journal of Energy Storage, Vol. 65)

$$C_{deg} = C_{deg}^{calendar} + C_{deg}^{cycle}\ [\%]$$

- **Calendar ageing** occurs passively due to chemical instability at the electrode-electrolyte interface, even when the battery is idle or in standby mode. It's influenced significantly by high temperatures and prolonged storage at high SoC, 2 of the key variables described earlier.

- **Cycle ageing** results from mechanical and electrochemical stress induced by repetitive charging and discharging, particularly at high DoD, high C-rates (charge/discharge speeds), or in extreme temperatures. This ageing as mentioned is due to the other key variable missing, DoD, as well as temperature.

The cumulative effect of both types of degradation leads to a gradual reduction in usable capacity and energy efficiency. Empirical studies, as the ones mentioned earlier in this section, show that under moderate usage conditions and controlled DoD profiles, lithium-ion batteries may experience annual capacity losses between 1.8% and 2.5%.

The State of Health (SoH) is directly related to the capacity degradation. SoH provides an indication of the battery's current performance relative to its original, nominal capacity. It encapsulates all forms of degradation, both calendar and cycle-related, and is used to track the effective ageing of the system. As the battery degrades, its SoH decreases, reflecting reductions in energy capacity, power output, and efficiency. A typical utility-scale battery may be considered to reach its end of life when SoH falls below 70–75%, although this threshold can vary depending on project economics and performance requirements. Accurate SoH monitoring is crucial for lifecycle management and planning reinvestment or repowering decisions.

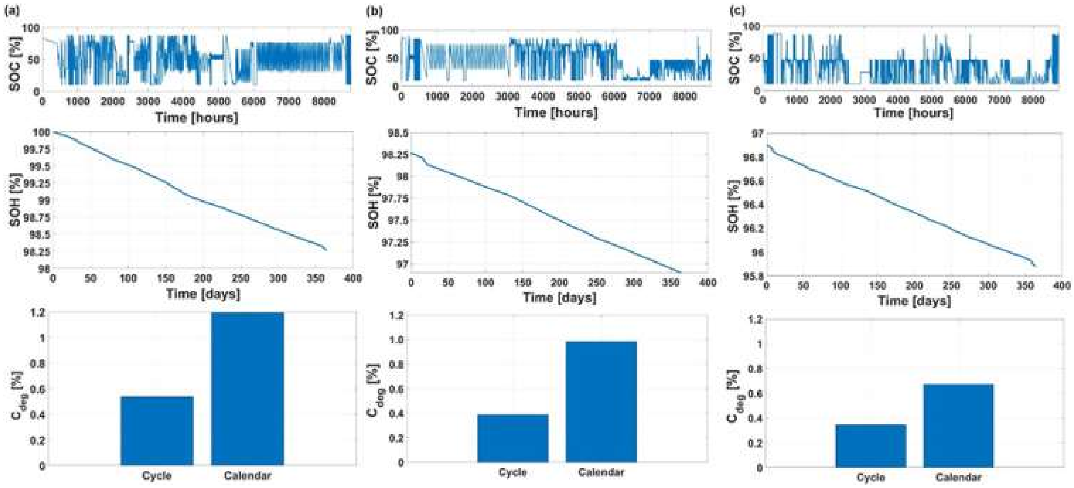


Figure 17. SoH and Cycle degradation throughout a 3-year test (Journal of Energy Storage, Vol. 65)

Overall, utility-scale lithium-ion batteries typically offer a calendar lifetime of 10 to 15 years or 4000 to 6000 full equivalent cycles, depending on the specific chemistry and operational regime.

Auxiliary Consumption and Internal Loads

In addition to the core energy cycling process, BESS installations incur internal energy consumption from auxiliary systems, including thermal management (HVAC), fire suppression, lighting, and the operation of battery management and control systems. These loads are essential for maintaining safe and efficient operation, especially in regions with high ambient temperatures. Cooling systems can consume a meaningful share of the total input energy, especially during peak summer months in Texas. Auxiliary consumption must be factored into the net energy output of the system, as it directly reduces the effective round-trip efficiency and impacts both operational costs and revenue projections in the model.

System Availability and Operational Hours

The expected availability of a utility-scale BESS system typically exceeds 95% and, in modern installations, can approach or surpass 99%. This figure accounts for scheduled maintenance, unexpected downtime, and limitations due to thermal derating or grid constraints. High availability is crucial for reliable participation in market services such as frequency regulation, and energy arbitrage, the two main sources of revenue for BESS projects in ERCOT. To maintain such performance, predictive maintenance and real-time diagnostics are often integrated into supervisory control systems.

Table 1 shows an executive summary of the key parameters discussed:

Table 1. Summary of Key Operational Parameters in Utility-Scale BESS

Parameter	Definition	Optimal Range/ Target	Impact on System Performance
State of Charge (SoC)	Percentage of total energy stored in the battery, reflecting available capacity at a given moment	20%–80%; Mid-SoC of 50% is ideal for degradation control	Avoids accelerated calendar aging from high SoC or resistance buildup from low SoC; helps extend battery life
Depth of Discharge (DoD)	Percentage of total capacity discharged during a single cycle, influencing wear on battery components	≤70% per cycle; balance needed between usable energy and longevity	High DoD accelerates cycle aging; lower DoD improves lifetime but may reduce energy throughput
Temperature	Ambient or internal battery temperature, which affects electrochemical reaction rates and safety	20–30 ºC container environment for best efficiency and aging mitigation	Low temps increase resistance and lithium plating risk; high temps speed up degradation and reduce life span
Round-Trip Efficiency (RTE)	Efficiency ratio of discharged energy to charged energy, including losses from conversion and heat	85%–93% depending on system design and ambient conditions	Higher RTE improves economic viability and increases usable output; key for IRR and profitability
Capacity Fade / State of Health (SoH)	Capacity fade is the gradual loss of energy-holding ability; SoH indicates performance relative to original capacity	SoH ≥ 70–75% is considered operational; fade rate ~1.8%–2.5% annually	Declining SoH reduces effective capacity and may trigger end-of-life replacement; drives maintenance planning
Auxiliary Consumption	Internal energy use for cooling, monitoring, lighting, and other support systems within the installation	Minimize HVAC share through efficient thermal design; varies with climate	Reduces net energy output and affects cost-efficiency; critical for OPEX and financial modeling
System Availability	Proportion of time the system is fully operational and available for dispatch and revenue-generating services	≥95% typical; modern systems aim for >99% uptime	High availability ensures revenue stability in energy and ancillary markets; critical for investor confidence

Understanding the technical characteristics of lithium-ion battery performance is essential not only from an engineering perspective but also as a foundational input for financial modeling, as it will later be shown on Chapter 3: Description of the Developed Model. Each parameter, whether round-trip efficiency, degradation rate, or auxiliary load, directly impacts the economic viability of a utility-scale BESS installation. A high-efficiency system with low degradation will yield greater usable energy over time, reducing levelized cost of storage (LCOS) and improving long-term returns. Conversely, systems subject to aggressive cycling, thermal stress, or suboptimal operating windows may face premature capacity loss, higher maintenance costs, and compressed financial performance.

2.3 ECONOMICS AND MARKET VIABILITY OF BESS IN ERCOT

Lithium-ion currently comprises 98% of grid-scale deployments, driven by its superior energy density, cost profile, and widespread manufacturing base. According to the International Energy Agency (IEA, 2022), lithium-ion batteries have decreased in costs from approximately \$1,100/kWh in 2010 to below \$150/kWh in 2024. Alternative chemistries such as sodium-ion, solid-state, flow batteries and iron-air batteries are emerging as potential competitors, offering promising advantages in longevity, safety, and cost-effectiveness, which in turn will continue developing the BESS market in favor of developers. Nevertheless, lithium-ion technology continues to lead in utility-scale applications due to its established supply chain and performance reliability.

Looking ahead, technological advancements are expected to further enhance the performance and cost-effectiveness of battery storage solutions. Emerging developments in artificial intelligence-driven dispatch optimization, grid-forming inverter technologies, and long-duration energy storage (LDES) systems are likely to redefine the role of BESS in the energy transition. The integration of solid-state and flow battery technologies could provide alternatives with improved safety and extended cycle life, while the adoption of machine learning algorithms for predictive analytics may further refine trading strategies. Moreover, the potential deployment of iron-air and liquid metal batteries, which offer discharge durations exceeding ten hours, could significantly expand storage applications beyond current market capabilities, as they could play a key role in non-spining reserve services, which must be sustainable for 4 hours, replacing power plants completely.

The financial viability of BESS projects is contingent upon multiple factors, including revenue stacking strategies, degradation rates, and operational costs. By leveraging multiple revenue streams, such as energy arbitrage, frequency regulation, and ECRS regulation, storage operators can optimize financial returns. However, battery degradation remains a critical consideration, necessitating advanced battery management systems (BMS) to extend asset lifespans and maintain efficiency levels. Economic projections for BESS projects in ERCOT suggest a CAPEX of approximately $750,000 per megawatt under moderate cost assumptions by 2027. These CAPEX projections come from NREL and will play a key role in the financial model of this project.

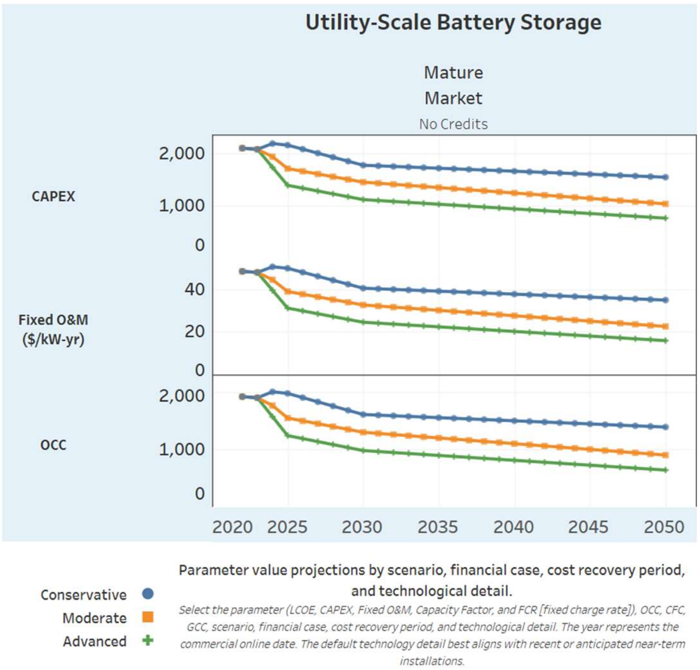


Figure 18. Utility-Scale Battery Storage costs projections based on 3 scenarios: Conservative, moderate, and advanced. (NREL, 2023)

The ERCOT market is uniquely structured among U.S. grid operators, as it operates under a fully deregulated framework with real-time nodal pricing and no centralized capacity market. This design has created favorable conditions for merchant battery storage developers who can capture value directly from price volatility, ancillary services, and arbitrage opportunities. ERCOT has also introduced specific mechanisms such as the Responsive Reserve Services (RRS), (comprising of Fast Frequency Response, Primary Frequency Response and Load Resource on Under-Frequency Relay, the latter not being well suited for batteries) which provides a tailored market product for high-speed resources like lithium-ion BESS, allowing them to participate more efficiently in frequency regulation. On the policy side, the Inflation Reduction Act (IRA) introduced a 30% standalone Investment Tax Credit (ITC) for energy storage projects beginning in 2023, a key financial enabler that has significantly improved project bankability across the U.S. (IEA, 2022).

As of 2025, ERCOT's battery storage interconnection queue has surpassed 90GW, highlighting rapid growth in developer interest. In parallel, firms like NextEra or ENGIE have announced multi-hundred-megawatt projects in the ERCOT pipeline, many designed to operate without Power Purchase Agreements (PPAs), relying instead on spot market signals and flexible dispatch strategies. This wave of investor-led development reflects both the revenue potential of storage in ERCOT and a growing appetite for merchant risk, supported by data-driven optimization and real-time analytics. The following table shows biggest BESS developers (or companies that have bought developed projects) in the interconnection queue as of late 2024.

Table 2. Companies, by size, that have BESS projects in ERCOT's interconnection queue

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 positive momentum, merchant BESS projects in ERCOT also face operational and financial risks that must be carefully considered. In recent years, ancillary services have played a key role in BESS revenue generation within ERCOT, particularly through frequency regulation products such as Regulation Up (Reg-Up), Regulation Down (Reg-Down), and the more recently introduced Enhanced Contingency Reserve Service (ECRS). Since its launch in June 2023, ECRS has delivered some of the highest revenues per megawatt for storage resources, with BESS comprising approximately 20-30% of its awarded capacity. However, market data from sources such as ModoEnergy indicate that the total ancillary services capacity is nearing saturation, with full saturation projected by December 2024. As auction competition intensifies, clearing prices are expected to decline, especially for short-duration systems competing against 4- to 8-hour installations better suited for ECRS requirements. This fierce competition in the ancillary services market may lead to price cannibalization, particularly for one-hour systems that rely heavily on regulation revenues. These trends reinforce the rationale for this thesis's focus on energy arbitrage as the primary revenue stream for modelling purposes, while treating ancillary service revenues as an upside potential rather than a base-case assumption.

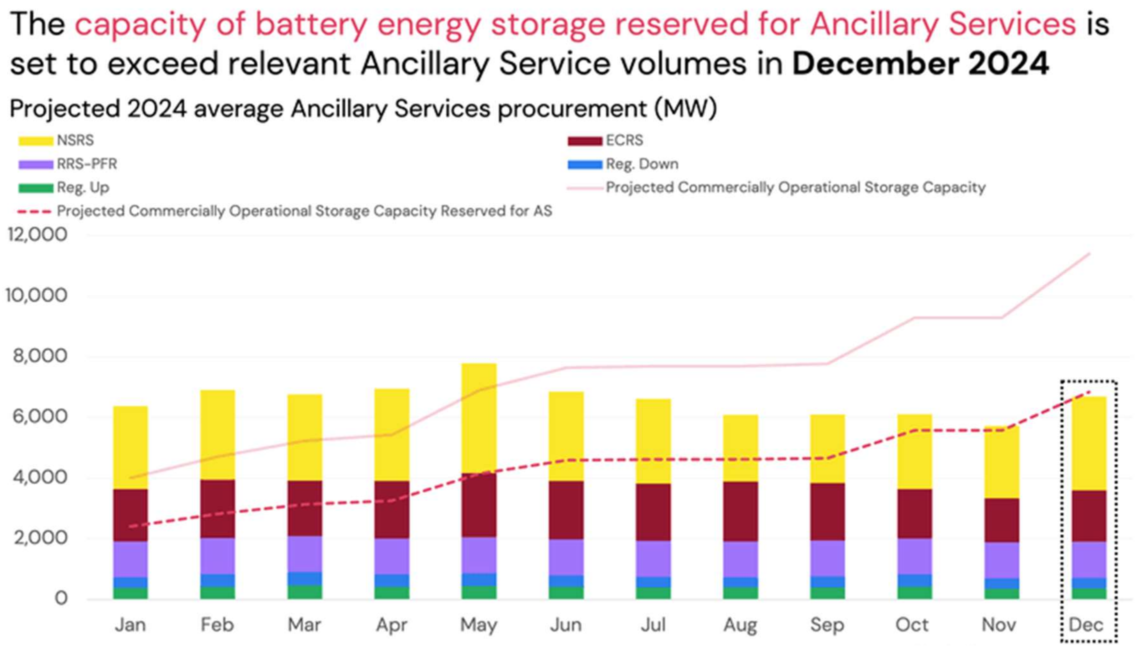


Figure 19. Projected ancillary services capacity saturation by the end of 2024 (ModoEnergy, 2024)

Additionally, real-time market volatility, while offering upside, can expose projects to unpredictable dispatch and revenue fluctuations, especially in nodes with limited congestion relief. These factors underscore the importance of location-specific modeling, degradation-aware dispatch strategies, and robust financial structuring to ensure long-term viability in ERCOT's fast-evolving energy landscape.

2.4 LIMITATIONS OF CURRENT PRACTICES IN ERCOT

As the ERCOT grid continues to evolve, battery storage systems are becoming an increasingly important tool to manage variability in renewable generation, relieve local congestion, and capture price arbitrage opportunities. However, despite the growing number of BESS installations, many current operational practices remain underdeveloped or overly simplistic, resulting in missed revenue potential and unnecessary technical degradation.

One of the most important and underexplored areas is the lack of locational dispatch optimization. In ERCOT, as mentioned above, prices are determined on a nodal basis, with over 17,000 unique settlement points, each influenced by local transmission constraints, supply-demand balances, and congestion. Despite this, many commercial BESS systems are developed and operated using average zonal or hub-level price assumptions, neglecting the significant variability between neighboring nodes. This oversight can lead to poor siting decisions, suboptimal arbitrage strategies, and ultimately diminished project economics. By contrast, a nodal-level optimization model, like the one presented in this thesis, enables developers and operators to anticipate locational price spreads and tailor dispatch behavior to the revenue potential of each individual node.

Another limitation lies in the underutilization of curtailment opportunities, especially in co-located solar + storage configurations in West Texas, where the region is known for its high levels of curtailment due to wind farms' PTC (Production Tax Credit), which leads to negative LMPs. Not only the negative pricing influence is caused by wind farms, with solar penetration growing rapidly in Texas, particularly in West and South ERCOT, the grid increasingly experiences midday price collapses and periods of negative LMPs when solar output exceeds demand or transmission capacity. While these conditions present ideal charging windows for BESS systems, many are either unaware of curtailment trends or fail to integrate them into their dispatch logic. The absence of curtailment-aware strategies means that valuable energy is left untapped, and developers are unable to fully monetize their generation. Incorporating historical curtailment patterns and real-time congestion signals into operational planning can unlock significant value, especially for two-hour batteries aimed at capturing peak ramping periods after solar drop-off.

In addition, current market practices often overlook the strategic potential of alternative storage technologies that could complement or eventually surpass lithium-ion systems. Flow batteries offer compelling advantages for long-duration applications, especially during periods of extended renewable surplus, thanks to their ability to discharge for 6+ hours, sustained cycle life, and inherently safer aqueous electrolytes. Unlike lithium-ion systems, where energy storage is fixed by cell capacity, flow batteries store energy in external electrolyte tanks, which allows independent scaling of power and energy capacity to suit specific use cases, making dimensioning even more precise than it is with lithium-ion batteries. According to the BCC Research blog, global flow-battery systems are well suited for grid-level, multi-hour storage and are seeing rapid advancements in both electrolyte chemistry and stack design. These systems also boast lower fire risk and longer operational lifespans, often between 25-30 years compared to approximately 15-20 years in typical lithium-ion deployments. One of the most key aspects of flow batteries are the different material battery types there are: All-vanadium, Zinc-bromine, lithium-ion flow batteries, etc. This in turn could decongest the massive demand there is for lithium-ion now, which could reduce a possible future shortage of said material.

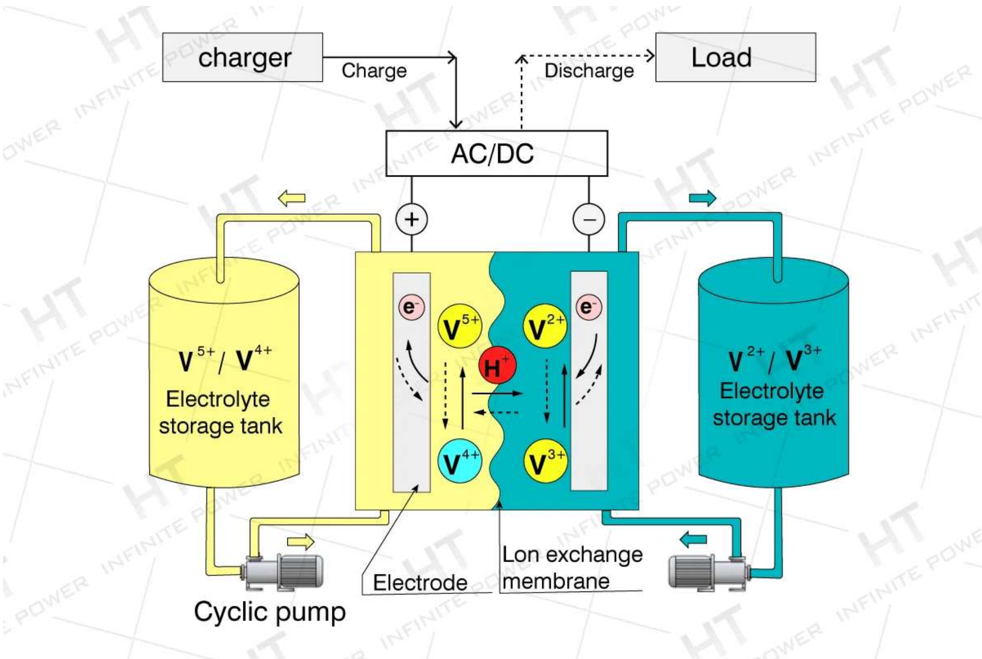


Figure 20. Flow battery schematic (Infinite Power, 2024)

As the ERCOT market approaches saturation in short-duration services, the economic case for LDES is gaining traction. In nodes experiencing frequent renewable oversupply and extended ramp events, flow batteries could provide value that lithium-ion systems struggle to capture, primarily through extended energy shifting without undue degradation or safety risk. While lithium-ion remains the backbone of current deployments, advancements in flow-battery economics and performance may soon present a viable alternative for selected ERCOT applications. Moreover, the flow-battery market is projected to grow from roughly US $417 million in 2024 to over $1 billion by 2029, representing a compound annual growth rate of 21.7%.

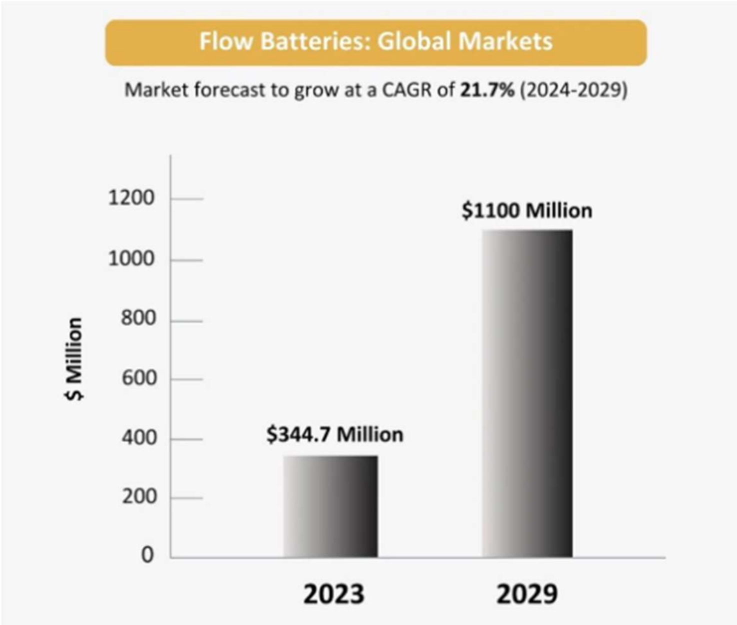


Figure 21. Outlook of Flow batteries market growth 2024-2029 (BCC Research, 2023)

However, despite these advantages, flow batteries currently face three main challenges that limit their immediate competitiveness in the utility-scale market. First, they tend to have higher upfront capital costs, largely due to the need for specialized stacks, tanks, and supporting infrastructure. Second, their lower energy density compared to lithium-ion means that more space is required to store the same amount of energy, making them less practical in land-constrained sites or compact installations. Lastly, the systems themselves are more mechanically complex, relying on pumps, valves, and continuous liquid circulation, which introduces additional points of failure and can increase both maintenance demands and operational oversight.

Moreover, most current BESS systems do not incorporate degradation-aware dispatch, a factor that has growing relevance as battery cycling frequency increases. Traditional dispatch algorithms often rely on simple threshold rules based on price signals or SoC targets, without considering long-term wear, thermal stress, or internal resistance growth. This leads to overly aggressive cycling, especially during periods of high price volatility, accelerating calendar and cycle degradation. In contrast, more advanced dispatch strategies adjust behavior based on real-time SoH indicators, ambient temperature, and historical degradation trends. These strategies may include limiting full charge/discharge cycles or shifting charging windows during extreme heat. While AI- and Machine-Learning based control logic is starting to gain traction in research environments, it is still rare in utility-scale commercial deployments, leaving significant performance gains unrealized.

These limitations, ranging from locational blindness to oversimplified dispatch logic, underscore the need for more sophisticated BESS project design and operational planning in ERCOT. By integrating site-specific price dynamics, curtailment behavior, degradation-aware control, and long-duration alternatives, the industry can move toward more resilient, efficient, and profitable storage deployments. The following chapter presents a modeling approach that seeks to address many of these gaps, offering a techno-economic framework for evaluating nodal battery performance in a highly granular and realistic ERCOT environment.

3. DESCRIPTION OF THE DEVELOPED MODEL

This chapter presents the development of a techno-economic model designed to evaluate and optimize battery energy storage system (BESS) deployment within the ERCOT market. Building on the research objectives introduced earlier, the model is technically framed to simulate the daily operation of a 2-hour lithium-ion battery under realistic market conditions, using historical Day-Ahead Market (DAM) pricing data across ERCOT's 17,000+ nodes from March 2021 to September 2024. The model integrates dispatch logic based on price-driven cycling behavior, seasonal charging strategies, battery degradation mechanisms, and core financial metrics, including capital and operating expenditures, tax incentives, and cash flow analysis. By identifying high-value nodes and optimizing dispatch performance at a granular level, this modeling framework supports more informed investment decisions and promotes smarter BESS development across the ERCOT network.

3.1 DATA ARCHITECTURE

To simulate battery performance under real market conditions, a robust and scalable data architecture was essential. This model relies on ERCOT Day-Ahead Market (DAM) locational marginal pricing (LMP) data from March 2021 to September 2024, covering thousands of pricing nodes across the Texas grid. Given the scale and granularity of this dataset, roughly 16GB of structured price information stored across daily CSV files, building an efficient and automated pipeline was critical for both model accuracy and usability. In addition to historical price data, the model development benefited from access to detailed transmission capacity information provided by EPE (Electric Power Engineers). This included N-0 and N-1 ratings for ERCOT's transmission lines, which indicate the network's ability to handle additional generation or storage capacity under normal and contingency conditions. These data were cross-referenced with ERCOT's 2024 interconnection queue for BESS and solar projects, then georeferenced and converted into shapefile and .kmz formats for integration into EPE's Google Earth Pro platform. This mapping enables rapid visual assessment of both market attractiveness, through nodal price overlays, and physical interconnection feasibility. While these spatial datasets are not embedded within the financial model itself, they form a valuable complement to the techno-economic analysis, particularly for early-stage site screening and stakeholder discussions.

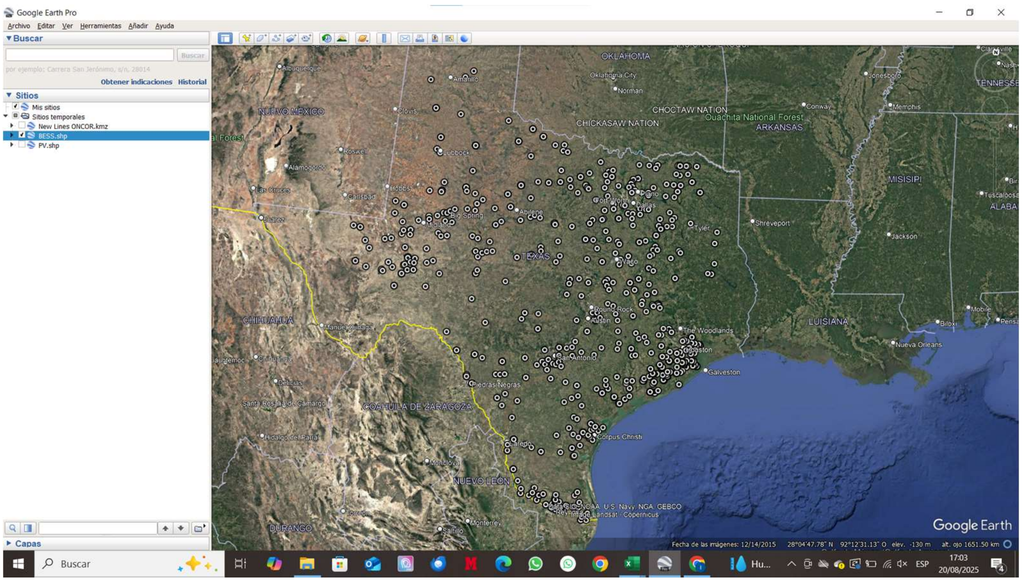


Figure 22. Mapped BESS 2024 interconnection queue into Google Earth Pro (white markers = projects)

The initial phase of model development focused on a subset of several thousand of the most relevant ERCOT nodes, specifically those for which Settlement Point Prices (SPPs) were available and consistent, mounting up to a total of around 1GB of price information across daily CSV files. DAM pricing data for each of these nodes was downloaded in .csv format from ercot.com, which was organized by separate day files, therefore an API was necessary to extract around 1,300 different .csv files from the website. To automate early-stage testing, a Python script using pandas and openpyxl was developed to sweep through daily price files, extract values corresponding to specific node names, and paste them into a centralized Excel spreadsheet. The user could input a desired node name into the Excel interface, and Python would extract its price history, enabling a simplified version of the dispatch simulation.

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 23. Initial template of data collection from .csv files located in separate folder

As the project evolved, the availability of complete daily ERCOT LMP datasets for all pricing nodes unlocked the potential for full-system simulations across the entire network. This allowed the model to scale from a few thousand SPPs to over 17,000 ERCOT nodes, covering the full set of LMPs published in the DAM. However, this expansion significantly increased the data load, making the Python-Excel pipeline inefficient for repeated queries. With over 3.9 million data points covering the full period, extracting data from raw CSVs became time-consuming, leading to the integration of a structured SQL solution.

This new architecture was built in SQL Server Management Studio (SSMS), where LMP data was organized into separate databases by year (LMP_2022, LMP_2023, etc.), for which each database had a table where all data from that specific year was included. Each table within each database was indexed by node name, date, and hour to enable rapid filtering and retrieval. This greatly enhanced performance: the Python script was modified to connect directly to the SQL database, fetch price data for a selected node, and forward it to the Excel model automatically. Now when the user entered a node ID in the Excel interface and pressed a macro button, Python executed a real-time query to SQL, retrieved the relevant pricing data, and populated the Excel sheet with historical hourly prices.

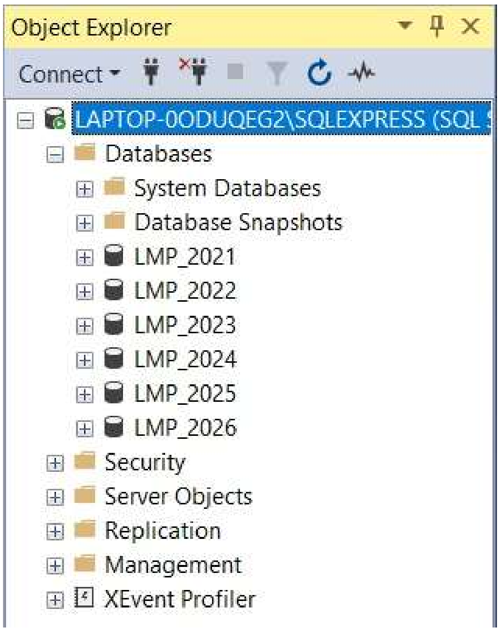


Figure 24. Separate LMP databases by year, with a .dbo LMP table located in each database containing yearly data

This SQL–Python–Excel structure not only increased the model's responsiveness, from several minutes down to roughly one minute per node simulation, but also made the system fully scalable to cover the entire ERCOT network. The automated pipeline allows users to simulate BESS dispatch strategies for any known ERCOT node, with outputs linked directly to both the techno-economic and financial calculations. By combining open-source tools and structured data handling, the model balances computational efficiency with transparency and user control. Not only that, but this code updating lead to the model in Excel running in a more smooth way, as now the data was loaded into a separate input sheet within the model, where data was referenced directly into the model, aiding in tables and figures being updated automatically.

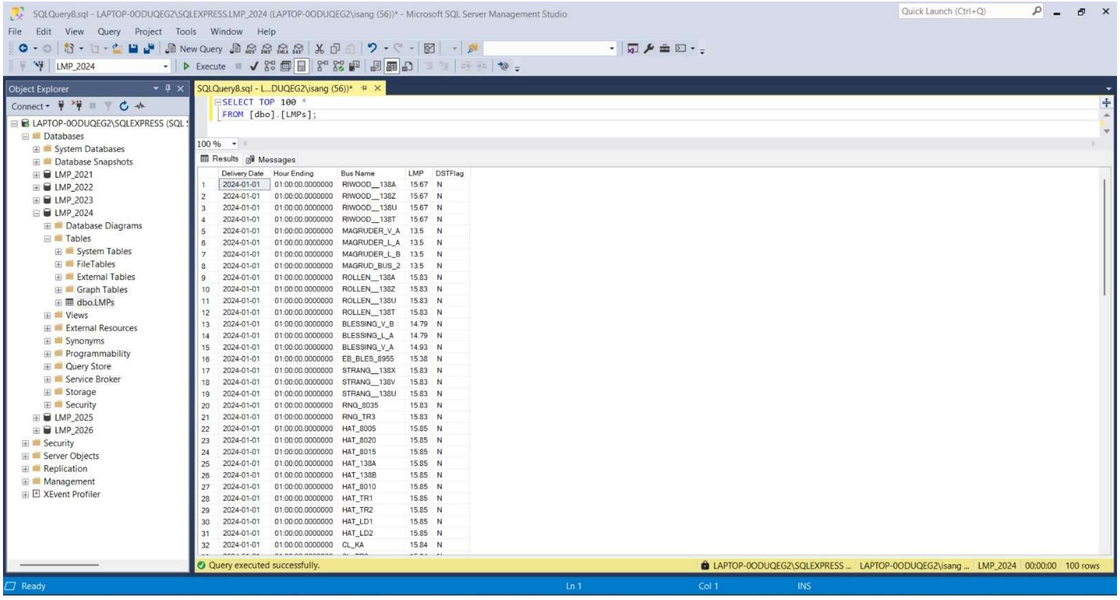
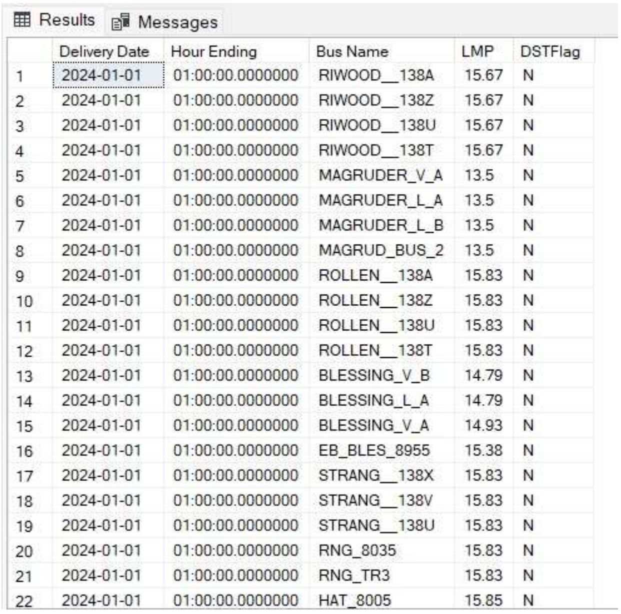


Figure 25. Data pipeline stored in SQL SSMS for the LMP_2024 database



	Delivery Date	Hour Ending	Bus Name	LMP	DSTFlag
1	2024-01-01	01:00:00.0000000	RIWOOD__138A	15.67	N
2	2024-01-01	01:00:00.0000000	RIWOOD__138Z	15.67	N
3	2024-01-01	01:00:00.0000000	RIWOOD__138U	15.67	N
4	2024-01-01	01:00:00.0000000	RIWOOD__138T	15.67	N
5	2024-01-01	01:00:00.0000000	MAGRUDER_V_A	13.5	N
6	2024-01-01	01:00:00.0000000	MAGRUDER_L_A	13.5	N
7	2024-01-01	01:00:00.0000000	MAGRUDER_L_B	13.5	N
8	2024-01-01	01:00:00.0000000	MAGRUD_BUS_2	13.5	N
9	2024-01-01	01:00:00.0000000	ROLLEN__138A	15.83	N
10	2024-01-01	01:00:00.0000000	ROLLEN__138Z	15.83	N
11	2024-01-01	01:00:00.0000000	ROLLEN__138U	15.83	N
12	2024-01-01	01:00:00.0000000	ROLLEN__138T	15.83	N
13	2024-01-01	01:00:00.0000000	BLESSING_V_B	14.79	N
14	2024-01-01	01:00:00.0000000	BLESSING_L_A	14.79	N
15	2024-01-01	01:00:00.0000000	BLESSING_V_A	14.93	N
16	2024-01-01	01:00:00.0000000	EB_BLES_8955	15.38	N
17	2024-01-01	01:00:00.0000000	STRANG__138X	15.83	N
18	2024-01-01	01:00:00.0000000	STRANG__138V	15.83	N
19	2024-01-01	01:00:00.0000000	STRANG__138U	15.83	N
20	2024-01-01	01:00:00.0000000	RNG_8035	15.83	N
21	2024-01-01	01:00:00.0000000	RNG_TR3	15.83	N
22	2024-01-01	01:00:00.0000000	HAT_8005	15.85	N

Figure 26. Closeup on data pipeline

Now, to achieve this data recollection from a specific node without having to write the node down in the code and execute the code, a macro button was inserted in a new 'Input sheet' within the model to run the economic dispatch once the specific node and the hub against which the node wanted to be compared to were selected. Pressing the 'Calculate Economic

Dispatch' button would link the excel to the python code to execute it, running down the whole modeling process in a button click:

Equation 2. Flow Diagram explaining modeling process through its data architecture

$$Button\ press\ \rightarrow Python\ activation\ through\ Excel\ Macro$$
$$\rightarrow SQL\ Data\ extraction\ from\ available\ databases\ through\ python\ command$$
$$\rightarrow Data\ load\ into\ existing\ model\ \rightarrow Dispatch\ calculation$$
$$\rightarrow New\ Excel\ saved\ by\ the\ name\ '"Node"\_BESS'$$

3.2 Modeling Assumptions

To ensure realistic and scalable simulation of BESS performance under ERCOT market conditions, the model incorporates a comprehensive set of technical, operational, and financial assumptions. These are based on industry standards for utility-scale lithium-ion batteries and tailored to ERCOT's nodal pricing environment and dispatch volatility.

Technical Parameters and Operational Strategy

Battery size is a configurable input, allowing project developers to tailor simulations to specific site constraints or land availability. Most of the simulations in this thesis are based on a 100 MW / 200 MWh configuration, but the model is flexible across sizes. The round-trip efficiency is set at 93%, consistent with current technology performance and aligned with expectations for near-future improvements. Base DoD is modeled at 95%, acknowledging more aggressive cycling to maximize economic value, while accounting for higher degradation rates in the financial outputs. State of Charge (SoC) is implicitly modeled assuming the battery is fully charged for the same number of hours as it is discharged, maintaining symmetry over long-term operation, leaving a modeled Mid-SoC of 50%.

The thermal environment is set at a constant 25 °C operational temperature, which aligns with optimal thermal control strategies for lithium-ion installations. This helps minimize thermal stress, stabilize internal resistance, and reduce the risk of accelerated aging. HVAC and auxiliary energy consumption are modeled as a flat 6% of potential annual energy revenues, serving as a proxy for SCADA, temperature control, and balance-of-plant operations. While this figure could fluctuate seasonally, it is conservatively kept constant across all simulation runs.

Battery lifetime is assumed to be 15 years for systems operating at 1.5 cycles per day and 20 years for systems constrained to one full cycle per day. Degradation is modeled as a combination of calendar aging and cycle aging, with an annual round-trip efficiency loss of 1% and a capacity fade of 1.95% per year at 95% DoD. The model allows users to vary DoD assumptions (e.g. 100%, 95%, 80%, 65%, or 50%) to evaluate trade-offs between energy throughput and degradation. These rates were benchmarked using findings from the Batteries 2020 study and serve as the technical backbone for projecting system performance over time.

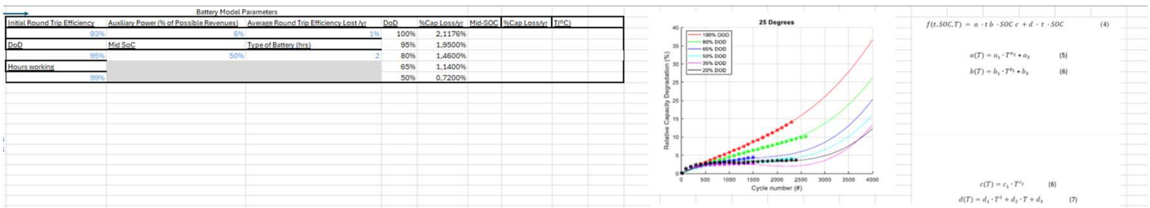


Figure 27. Technical parameters input in Excel, including degradation curves from scientific study used

The dispatch logic is seasonally adjusted based on historical ERCOT price behavior. As observed in the monthly average price profiles, May to September typically display a single peak around evening hours, while January to April and November–December show two clear peaks per day. The model integrates this variation by assigning 1 cycle/day in summer months and 2 cycles/day in winter months, with each daily strategy simulated using hourly average DAM prices over the full historical range. Simulations are conducted on a day-by-day basis, with price data pulled directly from SQL and used to dynamically assign charging (lowest price hours) and discharging (highest price hours) windows.

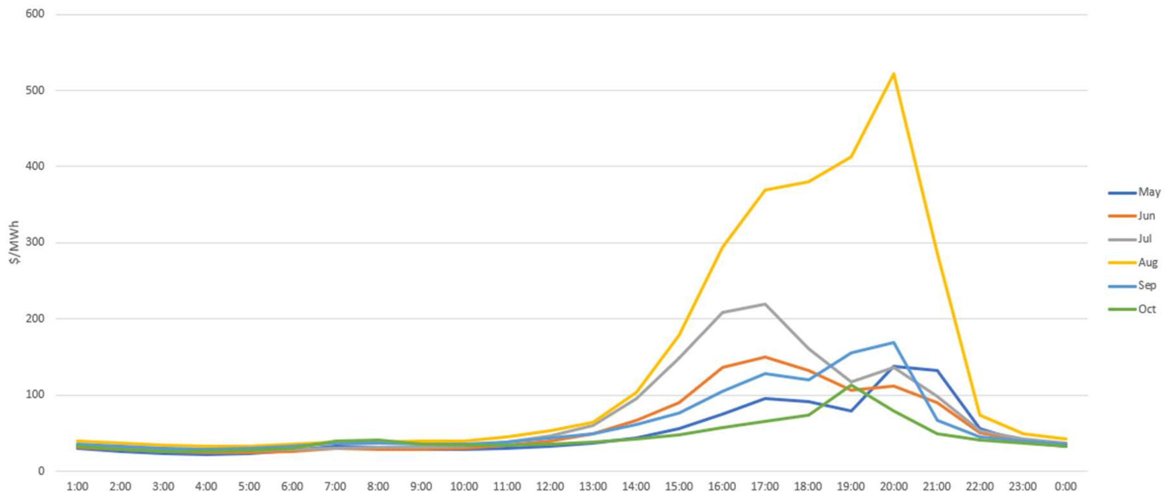


Figure 28. Average hourly LMP for a sample node in one-cycle modeled months

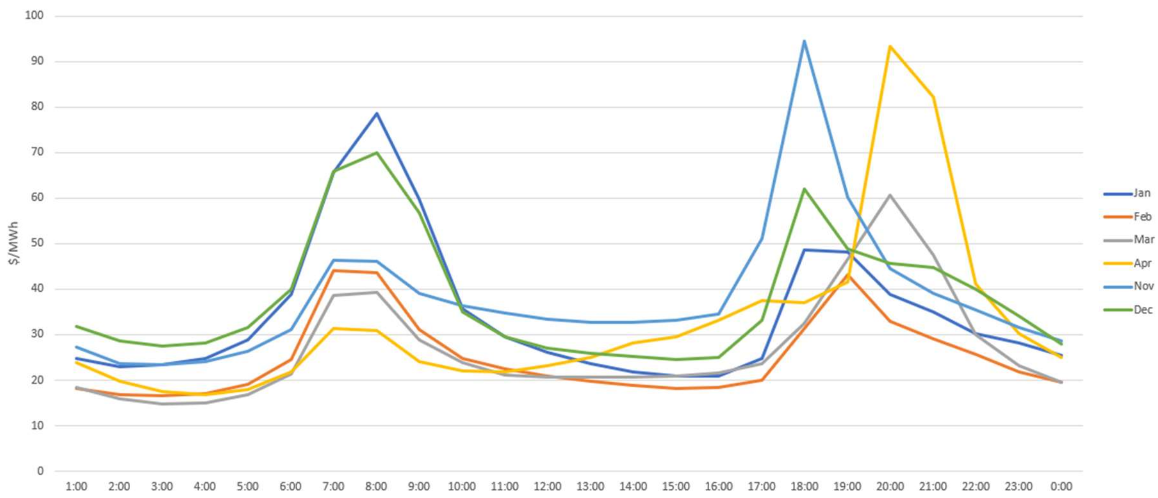


Figure 29. Average hourly LMP for a sample node in two-cycle modeled months

An additional feature of the model allows for an optional hybrid DAM–RT strategy. In this configuration, energy is acquired during the DAM's cheapest two hours, providing scheduling certainty, and discharged during the RTM's highest two price hours of the same day. While this approach assumes ideal foresight, being very optimistic to forecast with exactitude the two highest consecutive hours of the day, it serves as an upper-bound scenario for evaluating the potential benefits of integrating predictive machine learning models or day-ahead price forecasting engines into BESS control systems. This functionality is referred to in the model as the DAM-RT dispatch mode, and helps estimate the upside of future smart dispatch optimization tools.

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 30. DAM-RT modeling column example

Curtailment and Co-location Opportunity Estimation

To evaluate the value-add of BESS in co-located solar + storage scenarios, the model estimates economic curtailment using historical curtailment hour counts and ERCOT hourly DAM price profiles. This is done by calculating the sum-product of curtailed energy hours (in MWh) with the average DAM price at that same hour and month. This method provides a reasonable approximation of revenue lost per MW per year due to curtailment events in solar-only installations.

It's important to note that this figure represents only the value of lost energy at the time of generation. To put this into an example, if a specific hour of a day of a specific month the LMP where a solar installation is located experiences curtailment, the curtailment model values that "economic loss", or missed revenue, as the average LMP at which energy is sold at that hour in that month. This means that a BESS co-located at the same site can not only capture that curtailed energy, but shift it to higher-value hours later in the day, unlocking further upside not fully captured in this baseline. Therefore, this model treats economic curtailment as a lower bound on co-location opportunity, recognizing that real operational strategies may yield higher arbitrage value.

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 31. Curtailment heatmap by number of hours vs. Average hourly price in a month for that specific hour

To contextualize the co-location analysis, a standard hourly solar generation profile for a 100 MW plant in the ERCOT North Hub is applied. This region has seen the most solar development activity in Texas over the last decade and provides a representative benchmark for solar output patterns and overlap with curtailment-prone hours.

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 32. Generic 100MW ERCOT North Hub hourly solar profile in a given year

As a way of summarizing the modeling assumptions, the following summary table is shown to show all modeling assumptions in an organized and brief way:

Table 3. Modeling assumptions executive summary used in the Excel model presented

Category	Parameter	Value / Assumption
System Size	Battery size (MW/MWh)	User-defined; typically, 100 MW / 200 MWh
	Project lifetime	15 years (1.5 cycles/day) or 20 years (1 cycle/day)
Efficiency & Losses	Round-trip efficiency (initial)	93%
	Annual RTE degradation	1%
	Auxiliary/HVAC loss	6% of potential annual energy revenue
	Battery operating temperature	Fixed at 25 °C for thermal stability
Battery Degradation	Depth of Discharge (DoD)	95% (configurable down to 50%)
	Capacity fade rate	1.95% per year (at 95% DoD)
	End of life SoH threshold	70%
	Aging factors considered	Both calendar and cycling aging
State of Charge (SoC)	SoC modeling approach	Balanced daily charge/discharge (50% average SoC)
Dispatch Strategy	Seasonal cycling approach	1 cycle/day (summer), 1.5 cycles/day (winter months)
	Price data granularity	Daily average hourly DAM prices
	Dispatch rule	Charge during 2 cheapest hours, discharge during 2 peak hours
	DAM–RT hybrid option	Optional: DAM purchase + RTM discharge using ideal foresight

Financial Inputs	CAPEX & OPEX	Based on NREL cost curves (scenario-specific), OPEX = 3.5% CAPEX
	Tax incentives	30% ITC deducted from CAPEX
	Depreciation model	U.S. MACRS-style depreciation
Co-location Modeling	Curtailment value estimation	Sum-product of curtailed hours × DAM price (hour/month)
	Additional value from time-shifting	Recognized as upside beyond base curtailment revenue
	Solar generation profile	Hourly profile for 100 MW system in ERCOT North Hub

3.3 ALGORITHMIC LOGIC

The core of the model lies in its ability to emulate real-world battery dispatch behavior using historical ERCOT price signals while ensuring technical realism and computational efficiency. The algorithm is designed to simulate daily charge–discharge cycles based on actual hourly LMP data, apply seasonal dispatch logic, and integrate degradation and financial outputs in a modular, scalable way.

At its foundation, the model scans hourly Day-Ahead Market (DAM) prices for each node across a historical period ranging from March 2021 to September 2024. This data is stored as 24 rows per day, with each row representing a single hour's LMP. The VBA macro, triggered via an Excel button, processes this data row by row to simulate BESS operation over time. For each 24-hour block, the macro identifies the two consecutive cheapest hours as the charging window, and the two consecutive most expensive hours as the discharging window. This pattern reflects a value-maximizing arbitrage strategy, initially constrained to one charge and one discharge cycle per day to reflect battery symmetry and avoid overuse, which was later seen to lack full optimality, where the seasonal one-cycle and two-cycle mentioned earlier came into place.

	January	February	March	April	May	June	July	August	September	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	September	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 33. Output average example for two cheapest and two most expensive hours a day per month

To enforce technical realism, the algorithm guarantees that charging and discharging blocks are symmetrical (i.e., two hours in and two hours out), and that no simultaneous charging/discharging occurs. Once the battery has charged for its designated window, it is locked from further charging until discharge is completed. This rule-based structure maintains a Mid SoC of approximately 50%, consistent with long-term operation and the assumptions defined in Section 3.2.

For each day in historical LMP dataset:

1. Scan 24 hourly prices (one row = one hour)

2. Identify 2 consecutive lowest prices → Charge Window

3. Identify 2 consecutive highest prices → Discharge Window

4. If in winter month:

Repeat steps 2–3 for second cycle (1.5 cycles/day total)

5. Store charge/discharge hours and associated price spread

6. Calculate energy arbitrage revenue for the day

End loop

Aggregate daily results → Monthly averages → Annual revenue

Apply annual degradation and round-trip efficiency losses

Export KPIs to Excel output file

Figure 34. Simplified Pseudocode of the Daily BESS Dispatch Simulation Input

After all daily cycles for selected node are simulated:

1. Aggregate charge and discharge windows → Monthly averages

2. Calculate daily revenue per MW from price spreads

3. Aggregate daily revenues → Monthly and Annual revenue

4. Apply annual degradation (capacity + RTE reduction)

5. Compute average energy throughput and SoC pattern

6. Compare node KPIs vs. selected ERCOT hub

7. Optionally run DAM–RT scenario and log separate outputs

8. Export all KPIs and revenue summaries to:

"NodeName_BESS.xlsx"

Figure 35. Output Generation Logic for BESS Node Simulation

Seasonal variability in price patterns is handled via hard-coded month-by-month logic. Based on consistent trends observed in multi-year ERCOT data, the model assumes 1 full cycle per day in May through October, and 2 full cycles per day in January through April and November–December. This corresponds to typical system stress and solar ramp-down dynamics across ERCOT, where single-peak and dual-peak price patterns alternate seasonally. Accordingly, the VBA macro applies either one or two charge–discharge blocks per 24-hour period, depending on the month being processed. All dispatch windows are stored in monthly vectors, which are used to calculate daily and monthly average revenue per MW of installed capacity.

Each simulation is run one node at a time, as defined by the user in a central Excel interface file called 2HR_BatteryValuation_LMP_SQL.xlsm. The user selects a node of interest, e.g., to assess a specific project lead in Houston, and specifies a hub for benchmarking. Once the button is pressed, Python first retrieves the node's full historical LMP profile from the SQL database and populates the Excel interface. Immediately after, the VBA logic is triggered, and the simulation begins. The system evaluates each day's prices, applies the cycle logic, and stores calculated monthly metrics. After the run is complete, the model generates a new output file containing the full set of BESS valuation results, titled according to the selected node (e.g., HoustonWestNode_BESS.xlsx). This output includes KPIs such as average daily revenues, monthly earnings, and financial indicators used in Section 3.6.

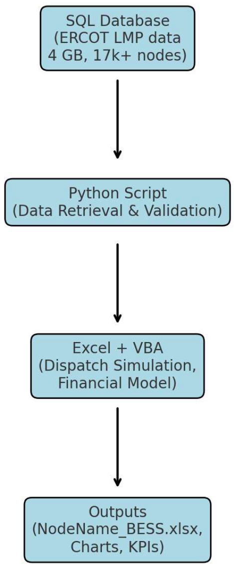


Figure 36. AI generated workflow architecture of BESS techno-economic model

The model applies degradation logic on an annual basis, which avoids unnecessary complexity while preserving realism in long-term financial projections. Degradation is modeled externally as an annual reduction in round-trip efficiency and usable capacity (as explained in Section 3.2), and these effects are applied after the revenue simulation. In this way, the model retains a clear separation between dispatch behavior and performance decay, which simplifies sensitivity analysis and allows for repeatable tests across nodes and configuration scenarios.

The logic also supports an optional DAM–RT hybrid dispatch mode, which can be toggled to explore upside from price forecasting and machine-learning-enabled dispatch strategies. In this configuration, the battery charges based on the two cheapest hours in the DAM, while discharging based on the two most expensive hours in the RTM of the same day. While this approach assumes perfect foresight and ideal execution, it serves as a theoretical upper bound for what could be achieved using advanced forecasting tools. The results from this mode are included in the financial analysis as a comparative benchmark to the base-case DAM-only dispatch.

Importantly, solar curtailment logic, solar curtailment, known as solar hours where the DAM price is below zero, is modeled independently from battery dispatch. The curtailment simulation, when activated, estimates the economic value of solar energy lost due to local transmission constraints, although unable to see exactly where those constraints come from in this model, or oversupply by summing curtailed hours against hourly prices. This allows users to explore co-location potential by comparing solar losses with BESS revenues at a given node. However, curtailment values are not treated as mandatory charging signals for the BESS; rather, they serve to assess whether co-located development makes sense based on independent performance of both subsystems.

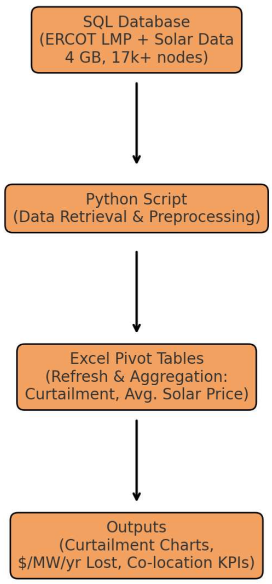


Figure 37. AI generated workflow architecture of curtailment model

3.4 TECH STACK

The developed model is built on an integrated architecture combining Excel/VBA, Python, and SQL, with each component performing a specific and complementary role. This configuration was reached through a process of trial and error, balancing technical capability, runtime efficiency, and ease of use for non-technical stakeholders. While Python and SQL handle large-scale data retrieval and processing, Excel and VBA remain the core environment for model execution, parameter adjustment, and results visualization, making the tool accessible to project developers and decision-makers without programming expertise.

Excel and VBA – Core Model Environment

Excel serves as the primary workspace, providing parameter input sheets, results dashboards, and graphical summaries of key performance indicators. The heart of the model — the daily dispatch simulation — is written entirely in VBA. This approach was initially chosen for its directness and readability: anyone opening the model for the first time can follow the logic without needing to understand an external programming environment. Once the VBA engine calculates annual revenue predictions based on energy arbitrage, embedded Excel formulas automatically populate the financial model, generating IRR, NPV, payback period, and other economic outputs. The user interface is designed for simplicity: a single button runs the entire workflow, and all tables and charts refresh automatically when a new node is simulated.

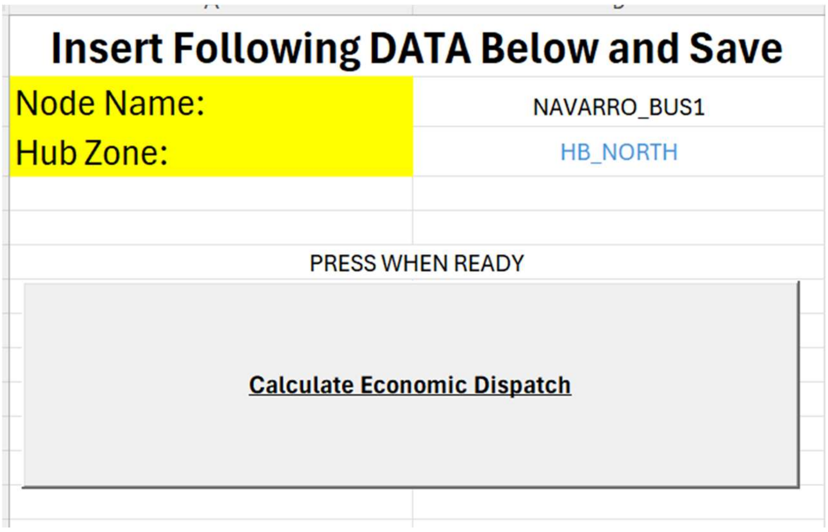


Figure 38. Excel interface with node selector and macro button

Python – Data Retrieval and Validation Layer

Python's role in the architecture is focused on the efficient extraction of historical price data from the SQL database. Using pandas, pyodbc, and openpyxl, the script retrieves the full hourly DAM price profile for the selected ERCOT node and passes it into the Excel interface. To ensure data integrity, the script includes security checks that verify the node exists in the database and that the expected number of hourly records per year (8,760) is present. If either condition fails, the process halts before any dispatch simulation begins. While Python's function is deliberately narrow in scope, this separation of tasks keeps the workflow modular and easier to maintain.

```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 39. Battery Valuation Python Script Extract

SQL – Large-Scale Data Management

The SQL database, hosted locally on a company workstation, contains more than 16GB of ERCOT locational marginal price data, covering over 17,000 nodes across approximately 3.5 years. Data is organized into annual tables (e.g., LMP_2022, LMP_2023) to optimize query performance. Before SQL integration, the model relied on CSV extraction and processing in Python, which required 5–10 minutes per node and placed a heavy load on RAM. SQL reduced retrieval times to roughly one minute per node, with minimal memory overhead, enabling faster iteration and making it feasible to run large numbers of simulations without overloading hardware, leading to close to a 90% runtime decrease.

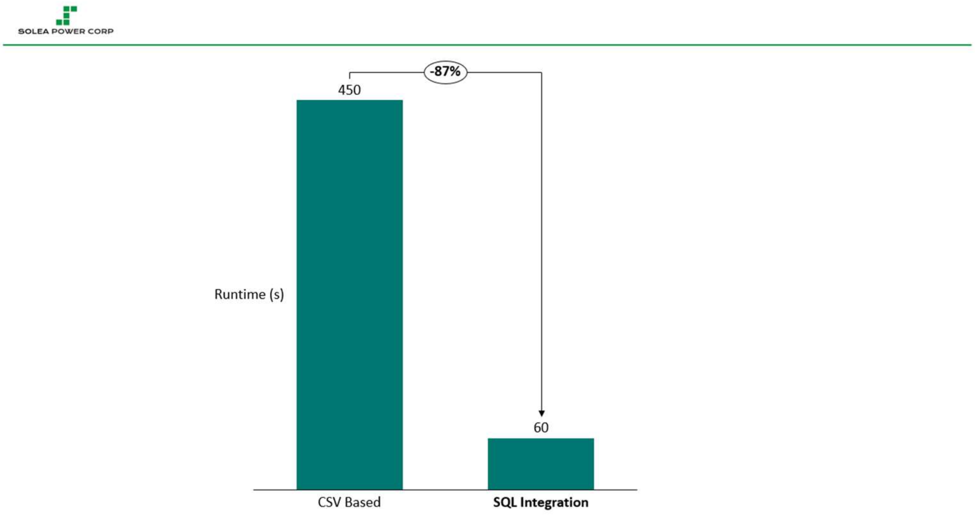


Figure 40. Comparison of average model runtime before (CSV Based) and after (SQL Integration)

Integration Workflow

The sequence is fully automated from the Excel interface. When the user selects a node and clicks the "Run Model" button, Python connects to SQL, retrieves the relevant dataset, and writes it into the Excel model. VBA then executes the dispatch algorithm, calculates daily and monthly revenues, and applies technical and financial assumptions such as degradation rates, round-trip efficiency losses, and cycle patterns. The complete results, including tables, charts, and a financial summary, are then saved as a separate Excel file named after the node (e.g., HoustonWestNode_BESS.xlsx). The same workflow structure is also used for the curtailment model, enabling seamless evaluation of co-location opportunities.

Scalability, Reproducibility, and Adaptability

The architecture was designed for both scalability and reproducibility. Adding a new year of data involves importing it into SQL under a new table and updating a single query in the Python script, without modifying the VBA dispatch engine. Similarly, the model can easily be adapted to work with Real-Time Market (RTM) data or to apply alternative dispatch strategies. For reproducibility, the system's design allows another analyst to operate it with minimal training: open the master Excel file, select a node and hub for comparison, press the run button, and retrieve results. By maintaining consistent output file naming and structure, simulations remain traceable and easy to archive.

```
' 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 41. VBA Code extract showing automatization of model dispatch, adapting to new data to be included in the future

3.5 FINANCIAL MODELING

The financial model in this study is designed to translate the technical and market performance outputs of the VBA-SQL-Python dispatch framework into a comprehensive, investment-grade cash flow projection. Its scope extends beyond simple revenue estimation, incorporating capital expenditure (CAPEX), operating expenditure (OPEX), tax incentives, depreciation, financing terms, and degradation assumptions into a single analytical environment. The model is structured as a project finance special purpose vehicle (SPV), in line with the prevalent practice in Texas where each large-scale renewable or storage project is developed under a separate legal entity, typically a limited liability company (LLC). By doing so, the model reflects real-world financing conditions, where lenders evaluate the project on its own merits and cash flows, without recourse to the parent company's balance sheet.

The primary objective of this financial layer is to determine the feasibility of a 2-hour lithium-ion BESS deployment under ERCOT market conditions, based on actual nodal Day-Ahead Market (DAM) price data. It evaluates both unlevered project internal rate of return (IRR), assuming 100% equity funding, and levered shareholder IRR, where cash flows account for debt service obligations. This dual-IRR approach allows for a more realistic assessment of investment attractiveness from both a total capital and equity investor perspective. The model also incorporates the 30% standalone storage Investment Tax Credit (ITC) and accelerated MACRS five-year depreciation schedule, both of which are critical in improving early-year cash flows and shortening the payback period.

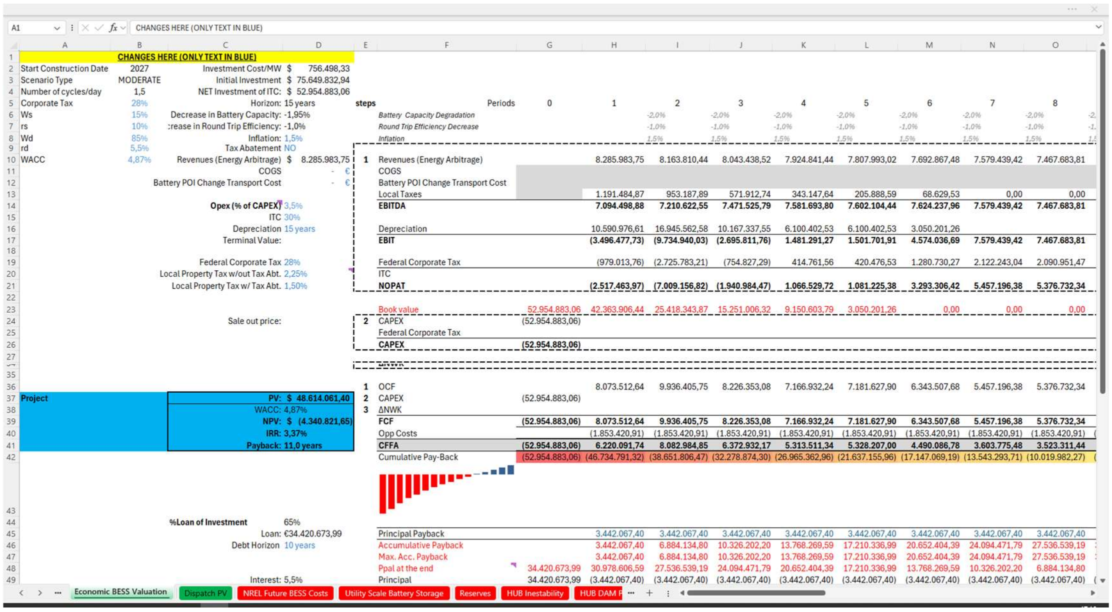


Figure 42. Extract of Financial model

System & Cost Assumptions

The base case assumes a 100 MW / 200 MWh utility-scale lithium-ion BESS, although the model is fully parameterized to accept any capacity size. CAPEX assumptions are sourced from the NREL BESS cost database under three scenarios, Conservative, Moderate, and

Optimistic, with Moderate being used as the default. These baseline costs have recently been adjusted in this thesis' model from 2026 onwards to reflect the U.S. tariff increases on Chinese imports announced in May 2024, which affect battery parts and non-EV lithium-ion batteries. The CAPEX breakdown, drawn from the NREL dataset, is presented to provide developers with visibility into the primary cost drivers, highlighting the proportion attributable to the battery system itself compared to the electrical balance of system (BOS), installation labor, EPC overhead, and other soft costs.

OPEX is modelled as 3.5% of total CAPEX per year, with 2.5% allocated to maintenance, covering routine servicing, corrective repairs, and minor component replacements, and 1% to insurance, which also includes provisions for battery module replacement in the event of premature degradation within the warranty period. Augmentation is not explicitly scheduled; instead, the system is operated until it reaches a reasonable state of health (SoH), at which point refinancing or capacity restoration could be considered. The model therefore reflects a "run-to-floor" operational approach rather than pre-programmed augmentation milestones, keeping early-stage cash flows as high as possible to front-load returns.

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 43. NREL-based Utility-Scale BESS Projections included in model (NREL ATB, 2020)

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 44. US Tariff Modifications on Chinese imports (US International Trade Administration, May 2024)

Policy, Tax, and Depreciation Assumptions

The financial model integrates the key policy mechanisms currently shaping the U.S. energy storage sector. A 30% standalone storage Investment Tax Credit (ITC) is applied directly to eligible CAPEX in the project's first year, significantly improving equity returns and reducing the required capital outlay. Accelerated depreciation is modelled using the Modified Accelerated Cost Recovery System (MACRS) five-year schedule, which front-loads depreciation benefits to the first half of the asset's life, used mainly in the US. This schedule allocates 20% in Year 1, 32% in Year 2, 19.2% in Year 3, 11.52% in Years 4 and 5, and 5.76% in Year 6, aligning with Internal Revenue Service guidelines for energy assets.

Federal corporate income tax is set at 28%, applied on earnings before interest and taxes (EBIT). In addition, two local property tax scenarios are modelled: a high-tax case at 2.25% of property book value per year when no tax abatement is given and a low-tax case at 1.5% with tax abatement. Property tax abatements are granted in certain Texas counties where the local governing authority deems the project beneficial to the regional economy, providing a meaningful boost to after-tax cash flows. Sales tax on equipment is accounted for within the CAPEX breakdown, and no separate recurring sales/use taxes are assumed during operations.

Financing Structure and Debt Assumptions

The model adopts a project finance special purpose vehicle (SPV) structure, with capital sourced from a combination of debt and equity at a 65% / 35% ratio, although with a dynamic option to change this debt-to-equity ratio. This mirrors common practice in the Texas renewable sector, where each project is ring-fenced under a dedicated LLC to limit investor exposure and enable debt to be secured solely against the project's own cash flows. The financing horizon is set to match the operational lifetime of the BESS, 15 years for the 1.5-cycle scenario and 20 years for the 1-cycle scenario, although debt is conservatively structured with a 10-year tenor. This shorter tenor reflects the potential reluctance of lenders to commit for the full life of the asset in the merchant-heavy ERCOT market.

Debt service is modelled at a fixed 5.5% interest rate with straight-line amortization, and no upfront financing fees are assumed. Reserve accounts such as a Debt Service Reserve Account (DSRA) or Major Maintenance Reserve Account (MRA) are considered implicit within the project's CAPEX, with no separate cash trapping in the base case. This approach maximizes distributable cash flow to equity in the early years, which is aligned with the model's strategy of capturing maximum value during the period of highest performance before degradation meaningfully impacts throughput. Both unlevered (project-level) IRR and levered (shareholder-level) IRR are calculated, allowing investors to assess returns with and without debt gearing effects.

Revenue Streams and Price Treatment

The financial model's revenue inputs are sourced directly from the VBA-based dispatch algorithm described in previous sections, ensuring a seamless link between nodal market performance and financial outputs. The base case assumes energy arbitrage solely within the Day-Ahead Market (DAM), where the battery charges during the two cheapest consecutive hours and discharges during the two most expensive consecutive hours each day. An optional Day-Ahead/Real-Time (DAM-RT) hybrid scenario is also included, in which charging is scheduled in DAM and discharging occurs in Real-Time during the two highest-priced hours of the day. While this DAM-RT approach is not used for the primary feasibility analysis, it serves as a useful "upside" test case, particularly if predictive analytics or machine learning algorithms are integrated in the future to anticipate high-price events in the Real-Time Market.

No ancillary services revenues are included in the base case, ensuring that the outputs reflect purely energy arbitrage potential. This conservative approach is deliberate, given that frequency regulation and reserve markets in ERCOT are becoming increasingly competitive, with revenue cannibalization already observed for short-duration assets. Price escalation is modelled at a nominal 1.5% per year for both energy prices and O&M costs, maintaining purchasing power parity over the life of the project. Revenues are inherently nodal in nature, with basis differences between hub and node already embedded in the VBA model output.

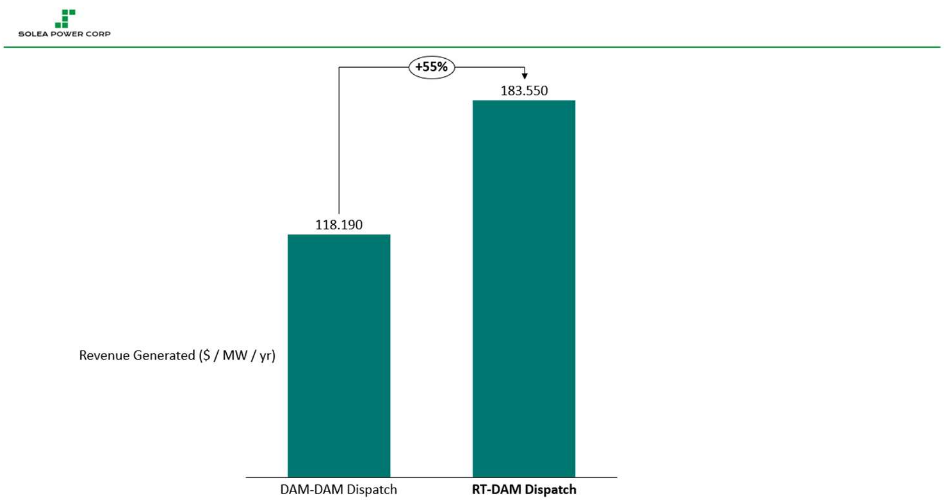


Figure 45. Example of revenue uplift /MW/yr from base DAM case to RT-DAM case

Performance, Degradation, and Availability Assumptions

Operational performance parameters in the model are calibrated to reflect their direct impact on annual energy throughput and, consequently, on project revenues and lifetime economics. The initial round-trip efficiency is set at 87% in Year 1, with a 1% annual decline factored into the revenue stream to reflect average conversion losses cited in different studies. This efficiency decay compounds with the 1.95% annual battery capacity fade, a function of the model's high depth-of-discharge assumption, reducing the energy available for sale over time. These losses directly erode gross revenues and, in later years, narrow debt service coverage ratios, making early-year cash generation critical to the project's financial resilience.

An HVAC load equivalent to 6% of annual revenue is modelled as a fixed OPEX deduction, capturing the cost of maintaining optimal operating temperatures. Availability is set at 99%, with the residual 1% downtime assumed for scheduled maintenance and unforeseen outages. While these operational metrics may appear modest in isolation, their cumulative effect over a 15- or 20-year horizon materially impacts both unlevered and levered IRR, as well as the net present value (NPV) of equity cash flows. By embedding degradation and availability directly in the annual cash flow calculation, the model ensures that payback profiles and sensitivity tests account for the inevitable decline in asset performance over time.

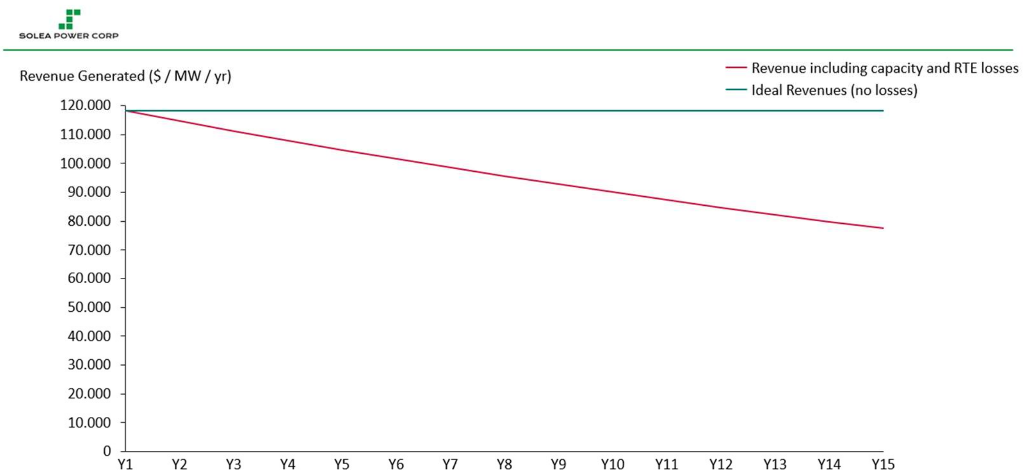


Figure 46. Example of impact on yearly revenues per MW with and without losses

Outputs, KPIs, and Sensitivities

The financial model produces a consolidated summary of project viability through a focused set of key performance indicators (KPIs). These include unlevered project IRR, levered shareholder IRR, net present value (NPV) at a weighted average cost of capital (WACC) consistent with market norms, and simple payback period. While the model runs on annual cash flows, Year 1 results also include a monthly revenue breakdown to provide seasonal insight into spread volatility. Equity cash flows are presented as a net of debt service for the levered case, allowing for direct comparison between project and shareholder returns.

Visual outputs are designed to make the financial implications of operational and market assumptions intuitive for decision-makers. A dynamic waterfall chart illustrates the path from gross revenues to equity cash flows, highlighting the proportional impact of OPEX, taxes, debt service, and policy incentives. A cumulative cash flow graph shows the breakeven year and total equity returns over the project life. Finally, a sensitivity "tornado" chart evaluates the effect of key variables, such as CAPEX, degradation rate, price escalation, and property tax scenario, on levered IRR, providing a quick diagnostic of which factors most influence bankability. Together, these outputs enable a comprehensive assessment of project economics that can be adapted to different nodes, system sizes, and financing scenarios at the push of a button.

Figure 47. Example of cumulative pay-back within BESS model

By integrating granular nodal price data with detailed cost, policy, and financing assumptions, the financial model bridges the gap between technical performance and investment decision-making. Its flexibility allows developers and investors to rapidly test site-specific economics, financing strategies, and operational parameters, producing results that are both market-reflective and investment-grade. The use of ERCOT's nodal Day-Ahead pricing ensures that location-specific value is captured, while optional DAM-RT and co-location scenarios provide a pathway to explore upside potential without overstating the base case. Ultimately, this modelling framework serves not only as a valuation tool, but as a decision support system, enabling stakeholders to prioritize high-return opportunities, mitigate financial risks, and align project development with long-term market trends in Texas's evolving energy storage landscape.

3.6 MODELING LIMITATIONS

While the developed techno-economic model is designed to provide a robust and location-specific valuation of BESS projects within ERCOT, several limitations must be acknowledged to ensure the correct interpretation of results. These limitations arise both from deliberate scoping choices, made to maintain model clarity and processing efficiency, and from external factors that could materially influence project economics but are not yet integrated into the framework.

The most significant limitation is the exclusion of ancillary services revenues, despite their historical importance in ERCOT's storage market. As of 2024, the total available ancillary services capacity is approaching full saturation, with projections from ModoEnergy suggesting this will occur by December 2024. In saturated conditions, auction competition forces participating BESS assets to bid lower to secure contracts, eroding the profitability of ancillary-only dispatch strategies. Enhanced Contingency Reserve Service (ECRS), introduced in June 2023, remains the most lucrative service on a $/MW basis, with BESS comprising 20–30% of its capacity. However, ECRS also favors longer-duration systems, typically 4- to 8-hour batteries, which fall outside the 2-hour lithium-ion scope of this thesis. By focusing on pure energy arbitrage, the model avoids overestimating revenues in a market segment where long-term sustainability is uncertain.

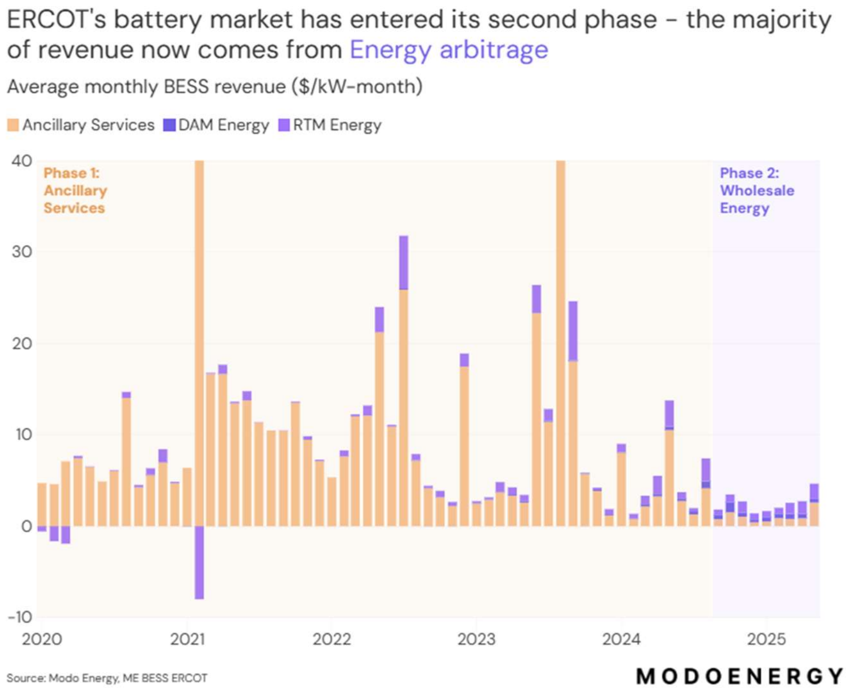


Figure 48. ModoEnergy study showing phase II of battery revenues, now focusing on energy arbitrage (ModoEnergy, 2025)

The model also does not account for transmission congestion management costs or potential transmission upgrades, which can be material in ERCOT's nodal market. On the other hand, recent news suggests important resource allocation in ERCOT to new 345kV and new 765kV lines to be built across Texas, with additional line capacity upgrades for 138kV and 69kV lines as well. While project viability inherently depends on interconnection capacity, these costs are excluded from the financial layer, as it will be assumed that no project will be placed in lines which need a self-financed line upgrade. However, through collaboration with EPE, nodal transmission capacity (N-0 and N-1 ratings) is known for each line in the ERCOT network. This information has been mapped against the 2024 interconnection queue of BESS and solar projects, with each line identified and converted into shapefile and .kmz formats for integration into Google Earth Pro, as shown in Figure 22 for BESS projects and the following figure for PV projects. This geospatial resource allows developers to visually assess both network capacity and market attractiveness when scouting potential project sites, an asset that complements, but is not directly embedded within, the techno-economic model.

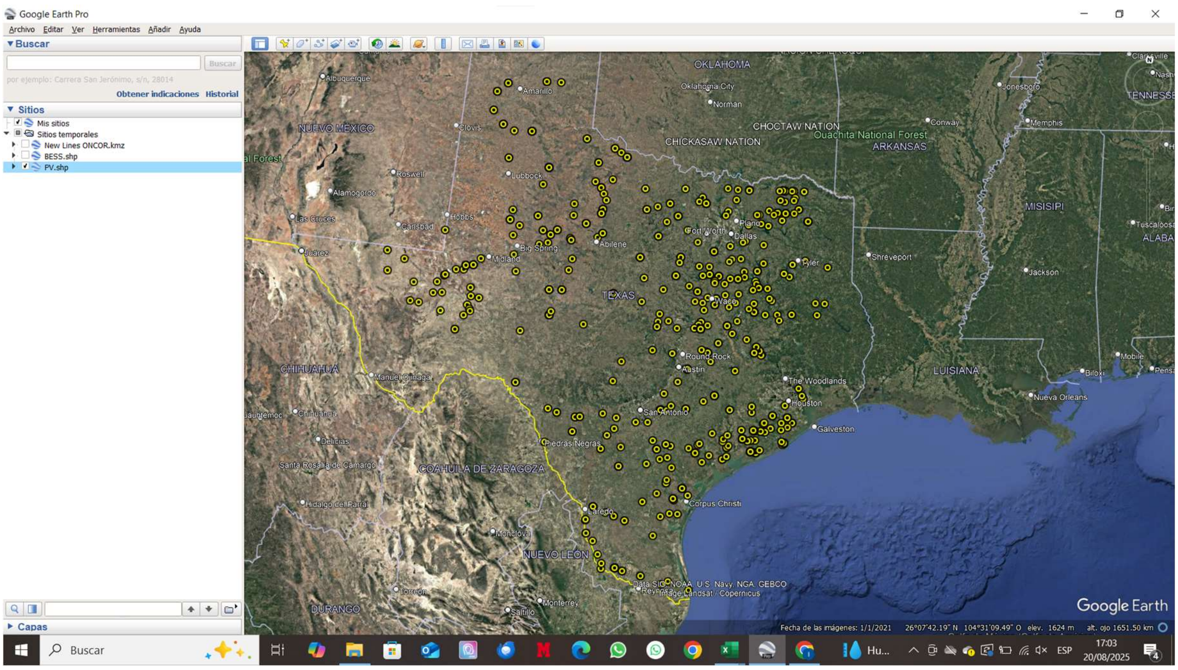


Figure 49. Mapped PV 2024 interconnection queue into Google Earth Pro (yellow markers = projects)

Technology scope is another limiting factor. The model is calibrated exclusively for utility-scale lithium-ion batteries, leveraging their current dominance in ERCOT's storage mix. Technical parameters such as round-trip efficiency, degradation, and HVAC loads are based on lithium-ion performance profiles at an optimal operating temperature of 25°C. HVAC energy consumption is fixed at 6% of annual revenues, contrasted once again with industry experts, assumed sufficient to maintain this temperature across all ERCOT climate zones when paired with proper insulation and CAPEX-allocated environmental controls. This assumption removes seasonal variability from the model, meaning that real-world deviations in auxiliary loads, especially during extreme Texas summers, are not reflected in cash flows.

Price data and dispatch logic also impose boundaries on the model's predictive capability. Revenues are based solely on historical Day-Ahead Market (DAM) price data (with optional Real-Time discharge in the DAM-RT scenario), without any forward-looking price forecasting. Seasonal cycle patterns, one cycle in summer months and two in winter, are hard coded by month based on observed historical trends, which may shift in future due to factors such as climate change. Projections for Texas suggest that average summer temperatures are rising, and winter peak demand patterns may change, which could alter the optimal seasonal dispatch profile in the coming decades.

Finally, the co-location and curtailment analysis is run separately from the BESS dispatch model. While this tool evaluates the economic value of lost solar output and potential battery capture, it does not integrate co-location revenues directly into the financial outputs. Moreover, the solar generation profile used in curtailment modelling is generic for the North Hub, ERCOT's most active solar development region in the last decade, and not node-specific or weather-year specific. This approach provides a reasonable baseline but may understate or overstate curtailment opportunities at individual sites.

Overall, these limitations underscore that the model is intended as a decision-support tool rather than a definitive profitability guarantee. Its value lies in identifying attractive nodes, testing operational strategies, and quantifying the impact of key technical and financial parameters, all while recognizing that broader market forces, evolving policy, and technological advancements will influence actual project performance.

4. RESULTS ANALYSIS

The results chapter applies the developed techno-economic model to real ERCOT nodes, illustrating how nodal conditions, solar resources, and market volatility shape the financial viability of BESS projects. To contextualize model behavior, two representative case studies are analyzed: Pamplona, located in the Houston Hub, and Santa Monica, located in the North Hub. These sites were selected because they align with strategic interests in ongoing project development, while also offering contrasting market conditions. Houston is characterized by higher price volatility and stronger solar resources, albeit within a land-constrained development environment. In contrast, the North Hub provides a more established region for solar and storage projects, with relatively stable nodal dynamics and lower solar yields.

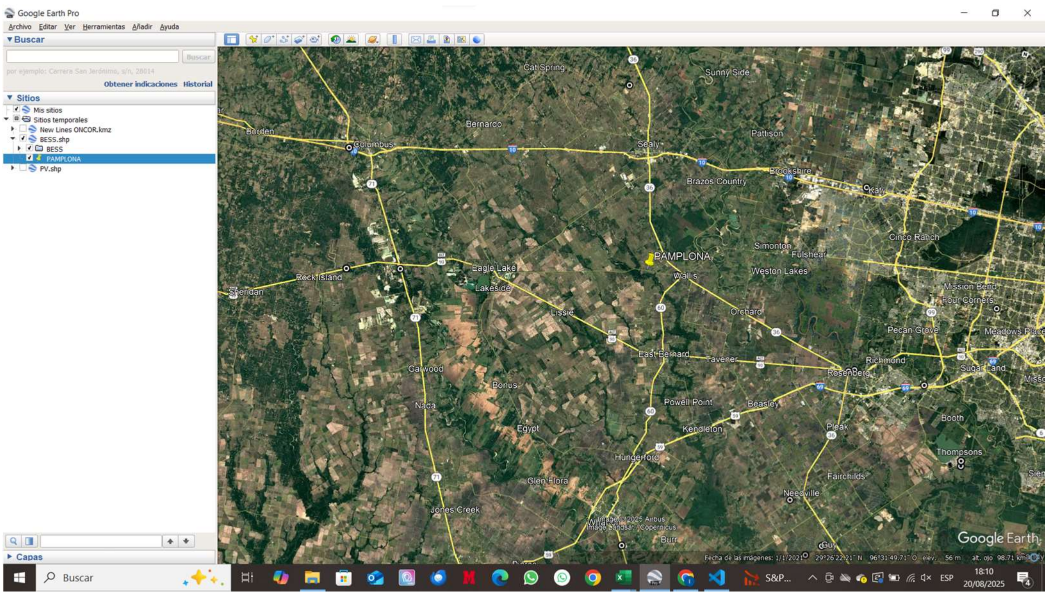


Figure 50. Pampona project location, West from Houston

Together, these case studies highlight how the same BESS configuration can yield differing outcomes depending on local market conditions, thereby reinforcing the importance of location-specific analysis. Following the node-level results, Section 4.2 expands the scope to a system-wide benchmarking across ERCOT's 17,000+ nodes, while Section 4.3

introduces sensitivity testing to assess robustness under varying technical and financial assumptions.

4.1 Base Case Node Analysis

This section evaluates the financial outcomes of the developed model at the node level for the two mentioned nodes. For each selected site, annual revenues, project and shareholder IRRs, and payback periods are presented. Results are then compared across nodes to illustrate how location-specific market conditions drive project feasibility.

4.1.1 Pamplona (Houston Hub)

Pamplona presents one of the strongest profiles in this study due to its high price volatility and spreads, which translate directly into enhanced arbitrage revenues. Under the base case assumptions, the model estimates annual revenues of $89,412 per MW / 2 MWh installation, yielding a project IRR of 4.93% (unlevered) and a shareholder IRR of 6.0% (levered). Payback periods are 10 years at the project level and 12 years at the shareholder level, making Pamplona one of the more financially robust nodes evaluated. Although these numbers don't look very attractive for investors, it has to be taken into account that this base model doesn't account for intraday trading and ancillary services revenue, so only with DAM-DAM dispatch those numbers look very interesting compared to the whole of ERCOT, giving a positive KPI comparison vs. ERCOT, which will be discussed later.

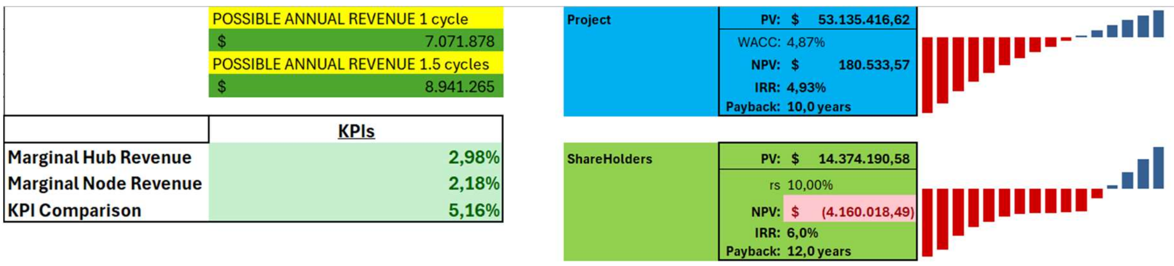


Figure 51. Pamplona Node (GEB_138A) Summary Sheet Results

From a solar perspective, Pamplona records an average solar price of $49.71/MWh, slightly below the Houston hub average of $50.06/MWh. Curtailment is negligible, at only 2 hours per year, far below the levels observed in West Texas nodes. Although this means co-location would not be driven by curtailment avoidance, there is a case for it if the available land exceeds BESS requirements. Under such conditions, EPC and interconnection synergies could make a combined solar + storage development economically compelling.

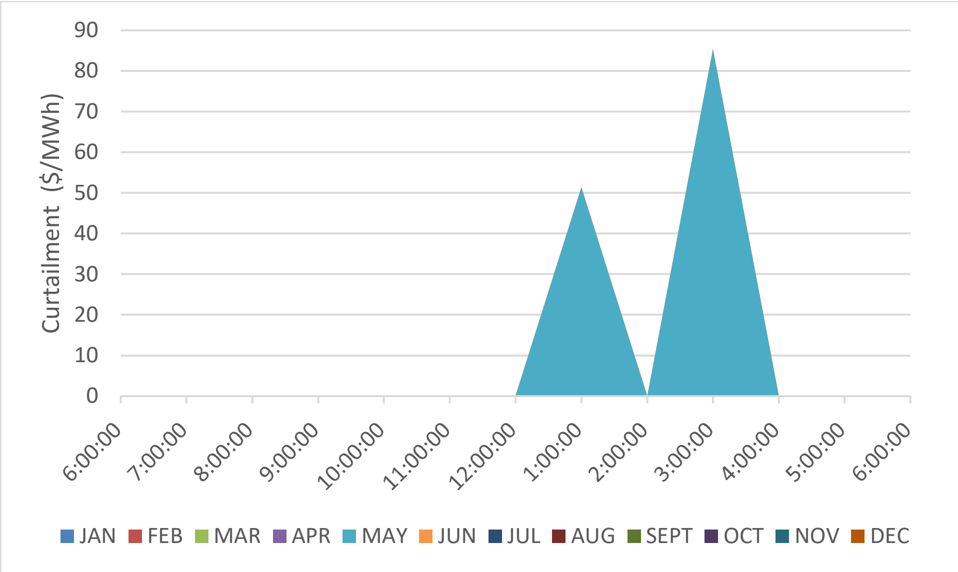


Figure 52. 2 Curtailment hours seen in Pamplona node, at a given day at 1PM and 3PM

4.1.2 Santa Monica (North Hub)

Santa Monica provides an instructive counterpoint. Annual revenues were $85,247 per MW / 2MWh, almost $4,200 lower than Pamplona per MW per year, leading to weaker financial returns: project IRR of 3.95% and shareholder IRR of 3.9%. Payback periods extended to 11 years (project) and 13 years (shareholders), reflecting thinner margins and higher relative risk. While technically feasible, the project's economics highlight the importance of node selection in ERCOT's volatile market.

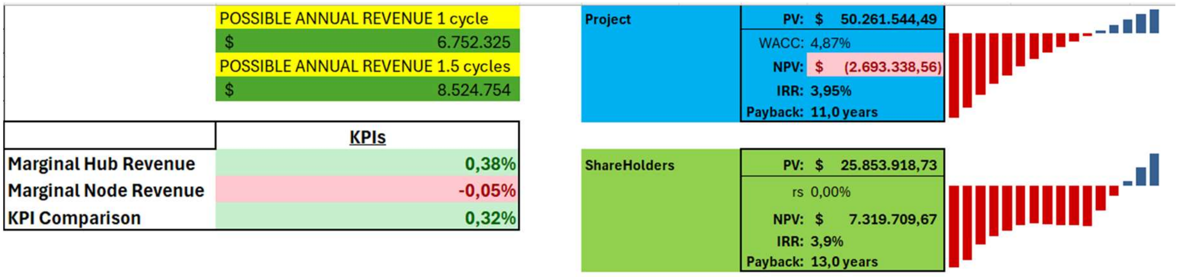


Figure 53. Santa Monica Node (Navarro_Bus1) Summary Sheet Results

Interestingly, Santa Monica's average solar price of $45.84/MWh is slightly above the North Hub average ($45.49/MWh). This made the site attractive for solar development, even if BESS economics were weaker. In practice, the node ultimately supported a solar-only project, illustrating how nodal conditions may favor different technologies. Curtailment at Santa Monica is negligible, meaning co-location would not provide significant incremental value beyond EPC or grid interconnection synergies.

4.1.3 Comparative Insights

The comparison between Pamplona and Santa Monica underlines how location-specific conditions shape feasibility. Pamplona's higher spreads and volatility support stronger BESS returns, while Santa Monica, despite a slightly more favorable solar price, produces weaker storage economics. This difference in economic viability is graphically seen by looking at monthly average daily revenues seen in both nodes.

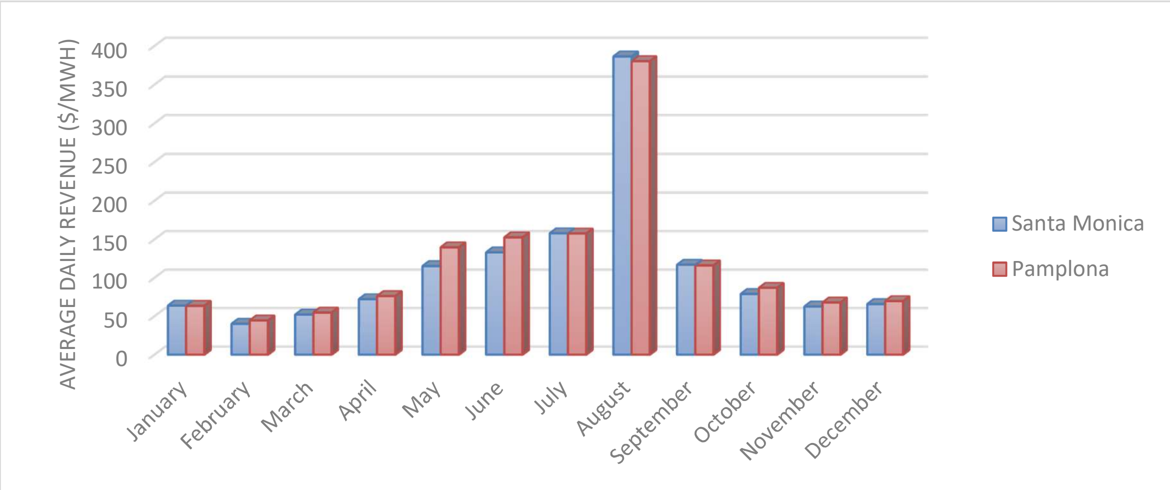


Figure 54. Pamplona vs Santa Monica average daily revenues per month ($/MWh)

It can be observed that Pamplona's node average revenues is higher for most months in comparison to Santa Monica, being one of the only exceptions the month of August, where intense heat waves are experienced more in the North Hub and volatility increases due to spikes in demand.

In addition, both nodes exhibit very low curtailment, meaning co-location decisions here are more a matter of synergies and land availability than curtailment relief. However, this is not the case system wide. In West Texas, curtailment can reach hundreds of hours annually due to high renewable penetration and transmission congestion, creating stronger incentives for co-located storage to capture otherwise lost revenues. While not the focus of this study, this contrast demonstrates why co-location potential must always be assessed in nodal context, and why a node-by-node analysis is crucial for developers.

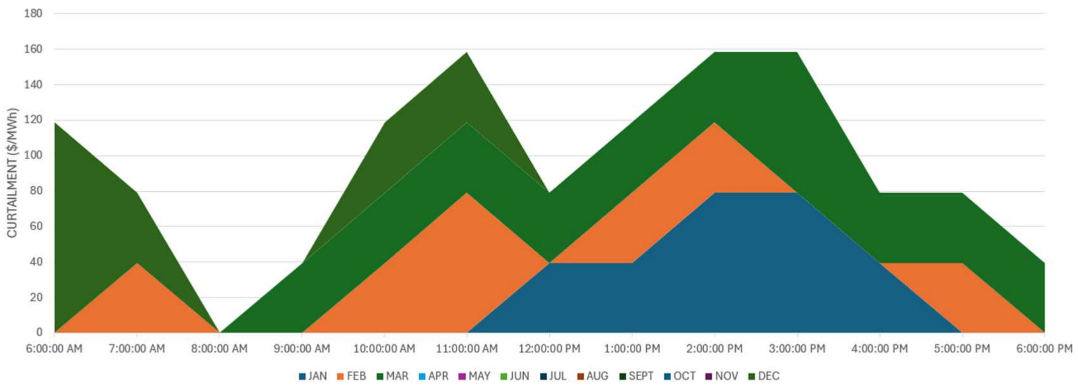


Figure 55. Example of Curtailment in an average West node (DUBLIN_8)

The following table acts as a summary of different financial and technical metrics between Santa Monica and Pamplona, which consolidate that in this case, Pamplona outperforms in this model to Santa Monica, and so it should be the main focus if an investor was to choose between the two.

Table 4. Metric Comparison Summary between Pamplona and Santa Monica nodes

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 (slightly < hub avg. 50.06)	45.84 (slightly > hub avg. 45.49)
Curtailment Hours (per year)	2	0
Solar Feasibility	Strong but secondary; EPC/interconnection synergies matter	Attractive solar-only; ultimately developed as solar
Co-location Potential	Conditional (if excess land & EPC synergies)	Minimal (curtailment too low, better as standalone solar)
Volatility Profile	High, strong spreads	Moderate, thinner spreads

4.2 SYSTEM-WIDE INSIGHTS FROM ERCOT BENCHMARKING

The comparative analysis between Pamplona and Santa Monica underscores the decisive role of nodal conditions in shaping BESS project outcomes. While both sites display low curtailment, their revenue profiles and IRRs diverge significantly due to differences in volatility and hub-specific dynamics. To move beyond individual case studies, the next section benchmarks result across ERCOT's 17,000+ nodes, providing a system-wide view of storage economics and highlighting where opportunities are concentrated.

4.2.1 Hub-Level Benchmarking

ERCOT is divided into 6 main hubs: North, South, Houston, West, Coastal and Panhandle. In this thesis, the main focus is on the first 4 hubs mentioned, as they're the most common hubs where projects are developed. Each hub generates has different price volatilities for each month of the year, with some hubs benefiting from winter daily revenues against the others (West Hub) whilst others benefit more on summer periods (Houston and North Hubs). The following figure shows average daily revenues per month for North, South, Houston and West Hub.

At the ERCOT-wide level, the average revenue across all 17,000+ nodes is $84,971/MW-year, which serves as a baseline reference for identifying above- and below-average hubs. However, hub-level conditions create meaningful divergences in BESS profitability, shaped by volatility, congestion, and curtailment dynamics.

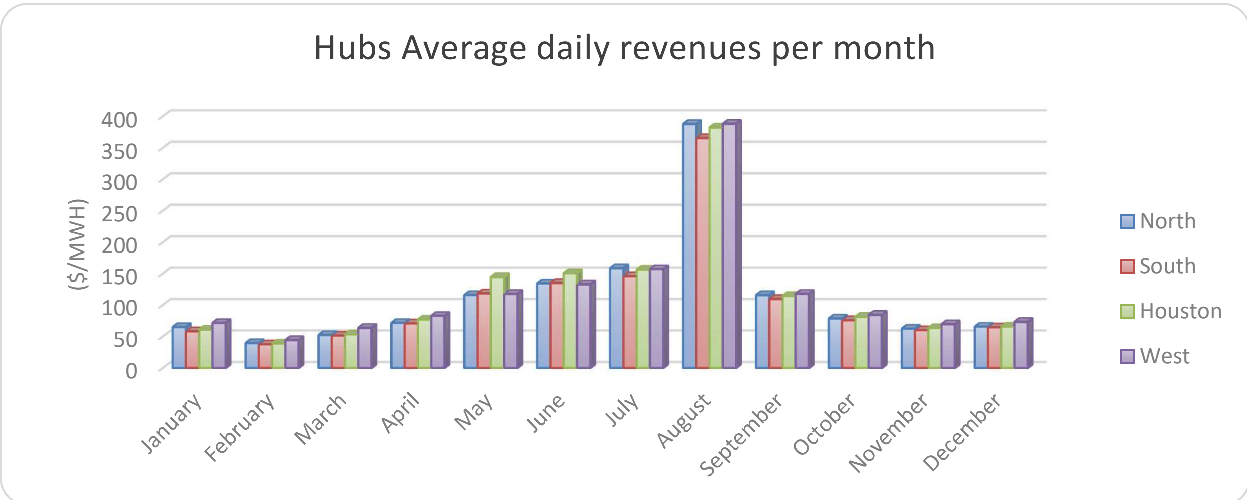


Figure 56. Average annual revenues across ERCOT Main Hubs, excluding Coastal and Panhandle

The West Hub records the highest benchmark at $90,497/MW-year, surpassing the system-wide mean by more than 6%. This reflects strong price volatility and arbitrage spreads, largely driven by high solar penetration and frequent congestion. Something also important to mention is the West's high level of curtailment due to the massive wind energy penetration through PTC, which lowers prices drastically in days of high renewable energy penetration.

This in turn means that not only BESS is interesting in the West Hub, rather that it could help existing solar installation to not stop production at any time due to curtailment, as BESS could absorb energy in periods of curtailment if co-located to a solar installation.

The Houston Hub follows with $87,505/MW-year, supported by high demand concentration and frequent scarcity pricing, as well as being a hub known for its frequent extreme weather events, especially frequent tornado appearance in the coast of Houston. While consistently above the ERCOT average, the hub faces significant land and interconnection constraints, making development more challenging. For developers who can secure land and transmission rights, however, Houston offers some of the strongest arbitrage opportunities.

The North Hub averages $85,290/MW-year, placing it close to the ERCOT-wide mean. Compared to Houston and West, its spreads are thinner, but its market is also less volatile, offering more predictable (though slightly lower) returns, which adds security to investments. This relative stability may appeal to more risk-averse investors, even if headline revenues are lower, meaning looking for an over the average arbitrage revenue node in the North Hub would be one of the most interesting projects in terms of low risk for investors.

Finally, the South Hub posts the weakest performance at $81,906/MW-year, roughly 3.6% below the ERCOT mean. Moderate spreads, combined with growing renewable congestion, reduce arbitrage margins, as well as the South Hub disposing of less industry and concentrated population, which lowers demand in the hub compared to other Hubs like the North Hub. On the other hand, for this hub, co-location with solar appears more promising than standalone projects, as BESS can capture value by storing otherwise curtailed generation.

Taken together, these benchmarks confirm that location is decisive for BESS feasibility in ERCOT. While West and Houston present the highest standalone revenues, they are constrained by high scale market uncertainty and grid bottlenecks. By contrast, North and South hubs trade profitability for greater predictability, for the North Hub or co-location potential for the South Hub. Developers must therefore balance revenue opportunity against operational challenges when selecting project sites.

4.2.2 Node Ranking & Relative KPIs

To complement the hub-level analysis, node-level KPIs provide a more granular perspective on project feasibility. To obtain a full node-level KPI, the KPI had to be split into 2 separate KPIs: Marginal Hub revenue, and Marginal Node revenue. The Marginal Hub revenue expresses how the hub where the project analyzed is located differentiates in revenue level to the global hub average, giving a KPI at hub level. For example, for this case, the West hub leads this KPI, with a +6.5%. On the other hand, to obtain the final node level, it has to be compared how the node's revenues differ from the hub's average it's located in. The following figure compares Pamplona and Santa Monica's node to demonstrate the difference in node quality for energy arbitrage between the two.

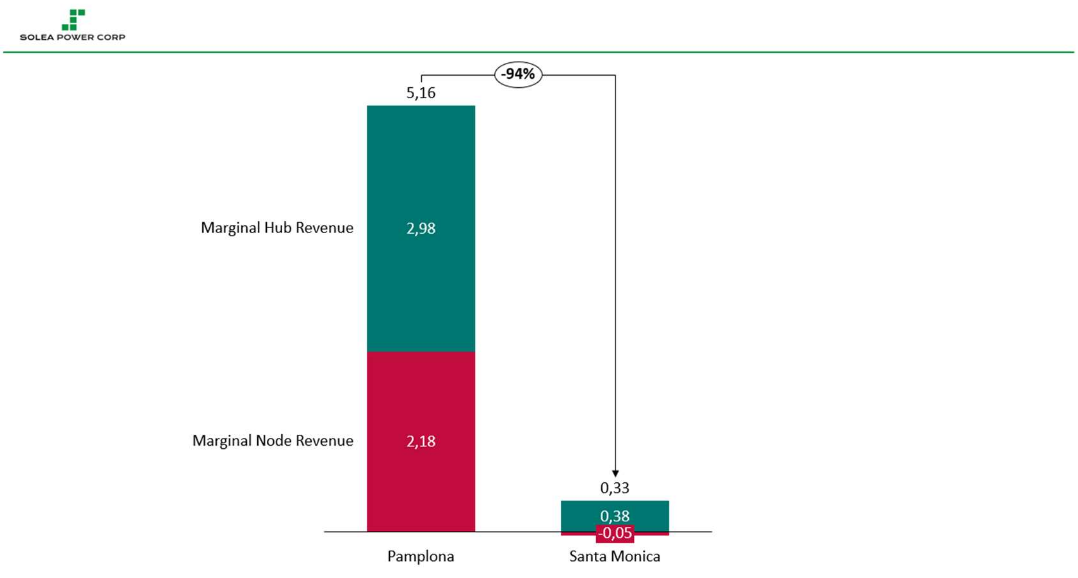


Figure 57. KPI value difference between Pamplona and Santa Monica, split into the two sub-KPIs

Pamplona demonstrates a clear competitive advantage, generating $89,412/MW-year, which is 2.2% above the Houston Hub average and 5.2% higher than the ERCOT-wide benchmark. This reinforces Houston's node overall attractiveness for BESS despite land constraints present, while also highlighting Pamplona as a strong outperformer even within its own hub, showing Pamplona as a very attractive target for BESS development.

By contrast, Santa Monica sits almost exactly at the North Hub average ($85,290/MW-year), showing virtually no deviation from its hub peers and only a marginal +0.4% above ERCOT average. Although this makes Santa Monica less of a standout performer, its relative stability and higher solar price compared to the hub average still mark it as an attractive site for solar-only or hybrid development, which is a separate theme from this thesis.

This comparison underscores three key takeaways. First, location matters: node-level dynamics can shift profitability by several percentage points even within the same hub, so it's important to analyze any node of interest separately, even if it's present in a hub in principle not as attractive as the other hubs. This leads into the second takeaway, that hub averages conceal wide dispersion; strong nodes like Pamplona can significantly outperform their hub peers, while others barely match averages. Finally, competitiveness must always be measured against the ERCOT system-wide average, as this establishes a consistent benchmark for BESS projects throughout ERCOT as a whole.

Together, these results show how ERCOT's nodal system rewards developers who optimize site selection at the most granular level. These KPIs intend to show a direct comparison between all 17,000+ nodes in ERCOT without having to deep-dive into project economics accurately. What this means is, that even if some assumptions are too conservative in the financial model, as long as a project in a node has seen to be viable in practice, this model can directly compare that node to any other node of interest, showing that if the node comparison results in a positive outcome vs the existing viable node, then there's a high chance the node analyzed might be profitable as well. To transition forward, it is important to note that while node KPIs highlight location-specific strengths, financial performance remains highly sensitive to technical and economic assumptions such as CAPEX, cycle depth, and market volatility. These sensitivities are addressed in the next section.

4.3 SENSITIVITY ANALYSIS (PAMPLONA CASE STUDY)

To better understand how operational and financial assumptions influence project outcomes, a sensitivity analysis was conducted on the Pamplona node in the Houston Hub. Pamplona was chosen as the reference point because it showed the most promising economics in the base case. By isolating this node, sensitivities can be clearly illustrated without duplicating analysis across multiple sites.

The analysis varies individual parameters while holding all others constant, to identify the drivers that most strongly affect project viability. Results are reported in terms of changes to IRR, payback period, and cumulative revenues relative to the Pamplona base case.

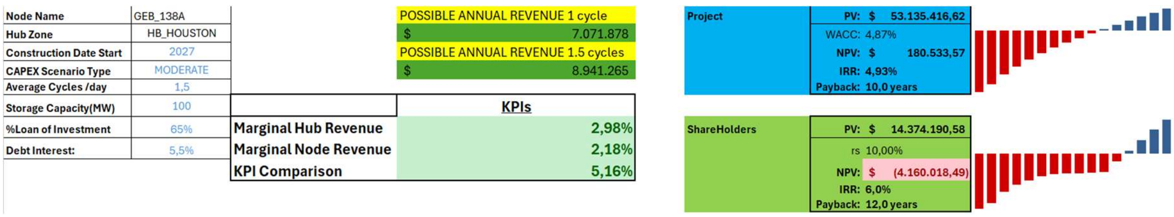


Figure 58. Pamplona Base Case Scenario

4.3.1 DAM vs. DAM–RT Dispatch

The most influential sensitivity factor was the choice of market participation strategy. Under a Day-Ahead Market only (DAM) scenario, Year 1 revenues for a 100 MW / 200 MWh installation at Pamplona reached approximately \$8.94 million, as shown in the previous figure. However, when simulating an ideal DAM–RT strategy, revenues jumped to \$14.68 million, an increase of 64%.

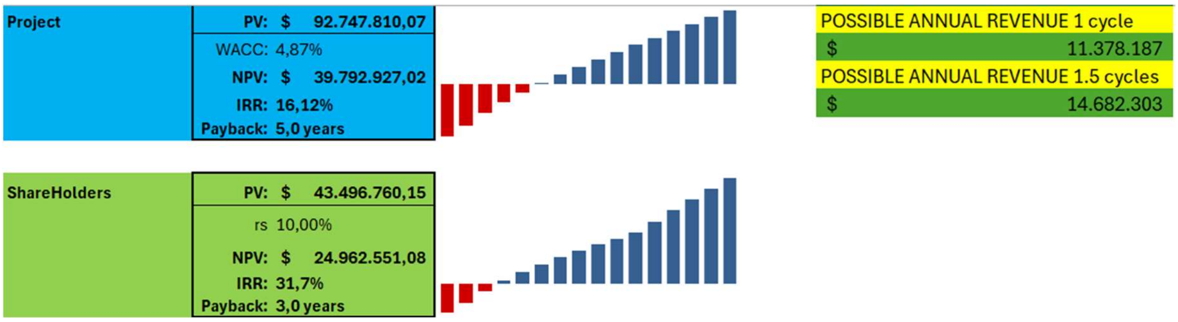


Figure 59. Pamplona ideal DAM-RT Dispatch Scenario

This revenue uplift translated into a project IRR increase from 4.9% to 16.1%, and a shareholder IRR increase from 6.0% to 31.7%, cutting payback times nearly in half (from 10–12 years to 3–5 years). These results illustrate the transformative role of predictive dispatch optimization. While the simulation assumes perfect foresight of real-time price peaks, advances in machine learning and AI forecasting suggest that ERCOT operators could realistically capture part of this upside in future years, exponentially increasing project viability.

4.3.2 CAPEX Scenarios (NREL Cost Paths)

In addition, Capital expenditure assumptions represent another critical driver of feasibility. Using NREL's 2019 projections, there are three CAPEX projection tiers to be analyzed. These are Optimistic, Moderate and Conservative. Bear in mind the base case used for past results display show the moderate case for an initial construction date of 2027. The other two scenarios give opposite results and differ heavily from the moderate scenario:

Both cases-maintained Year 1 revenues per an 100MW installation to $8.94 million. However, on one hand, Optimistic CAPEX (473 $/kW) increased the project IRR to 15.5% and the shareholder IRR to 30.1%, with payback shortened to six and three years, respectively. On the other hand, Conservative CAPEX (844 $/kW) sharply reduced feasibility, with IRRs falling to 2.7% (project) and 1.3% (shareholders). These results demonstrate that CAPEX reductions remain a structural enabler for BESS projects, much like the solar PV industry in its early growth phase. Without continued technological cost declines or federal incentives, BESS projects face difficulty achieving investment-grade returns. In fact, without the 30% ITC, the Pamplona project, and almost any node project as of now, would fall into negative NPV territory, making energy arbitrage alone insufficient to sustain viability.

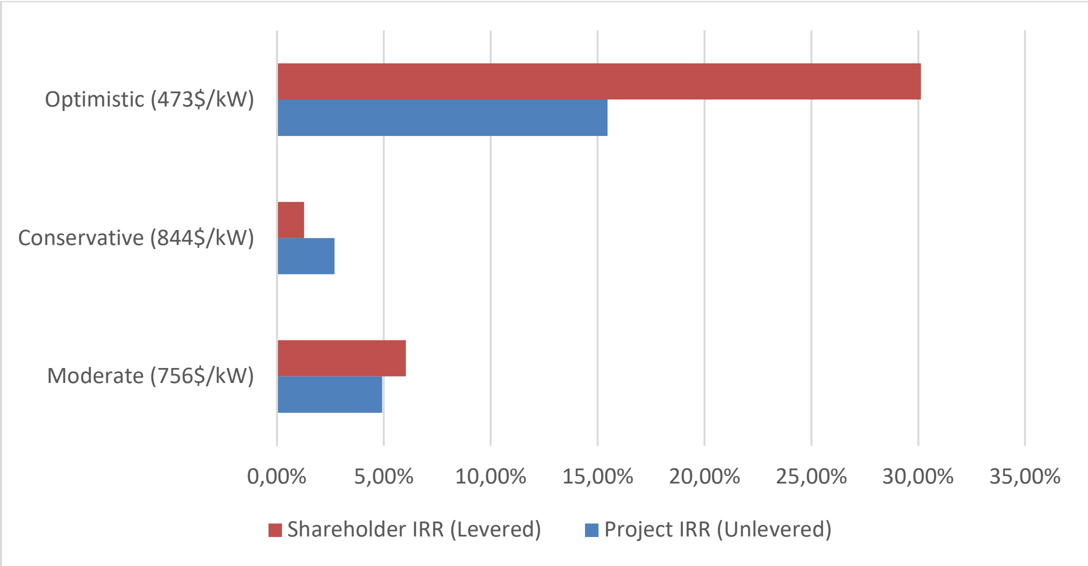


Figure 60. IRR shifts under different CAPEX scenarios

4.3.3 Technical Parameters

Although dispatch strategy and capital costs remain the dominant factors in determining project feasibility, the technical configuration of the battery also has a meaningful influence on financial performance. The analysis highlights how changes in cycle count, depth of discharge (DoD), and round-trip efficiency (RTE) affect revenues and investment metrics.

A first comparison was made between 1 and 1.5 cycles per day, using the winter period for 2 cycles and the summer period for 1 cycle as mentioned before in the model explanation. Moving from 1.5 cycles/day (associated with a 15-year project life) to 1 cycle/day (extending lifetime to 20 years) led to a sharp decline in Year 1 revenues, from $8.94 million to $7.07 million per 100 MW installation, equivalent to a 21% reduction and a significant reduction in IRR. While the longer horizon of a single-cycle strategy partly compensates, investors generally favor the higher near-term cash flows associated with 1.5 cycles/day, as these shorten the payback period and reduce exposure to long-term market uncertainties. Not only that, but that 21% reduction is very significant and shows the upside potential of taking advantage of the two daily peaks and two daily troughs in winter periods.

Depth of discharge (DoD) was also shown to materially affect project economics. At a high DoD of 95%, the battery captures maximum revenue potential. Reducing the DoD to 80% decreases Year 1 revenues to $7.53 million, a 15.8% decline relative to the base case, while project IRR falls to 3.8% and shareholder IRR to 3.6%. Further lowering the DoD to 65% reduces revenues to $6.11 million (–31.7%), driving IRRs below 3%. Although lower DoD settings extend technical lifetime by mitigating degradation, the associated reduction in usable capacity imposes a significant economic penalty, outweighing the long-term benefit.

RTE demonstrates a smaller, but still notable, influence on profitability. Improving RTE from 93% to 95% raises Year 1 revenues to $9.15 million, boosting IRRs to 5.4% (project) and 7.0% (shareholders). Conversely, reducing RTE to 91% results in revenues of $8.74 million (–2.2% compared to the base case), with a subsequent reduction in IRR as well. While these shifts are less dramatic than those produced by CAPEX or cycle settings, they underline the importance of incremental technical improvements in maximizing returns.

Taken together, these results suggest that technical refinements act more as value optimizers than as primary drivers of project feasibility. Higher RTE and carefully optimized cycle scheduling can enhance margins and accelerate payback, but they do not fundamentally alter the project's economic outlook. Instead, they are most effective when combined with stronger revenue levers such as DAM–RT arbitrage strategies or lower capital costs, where they serve to amplify already favorable conditions.

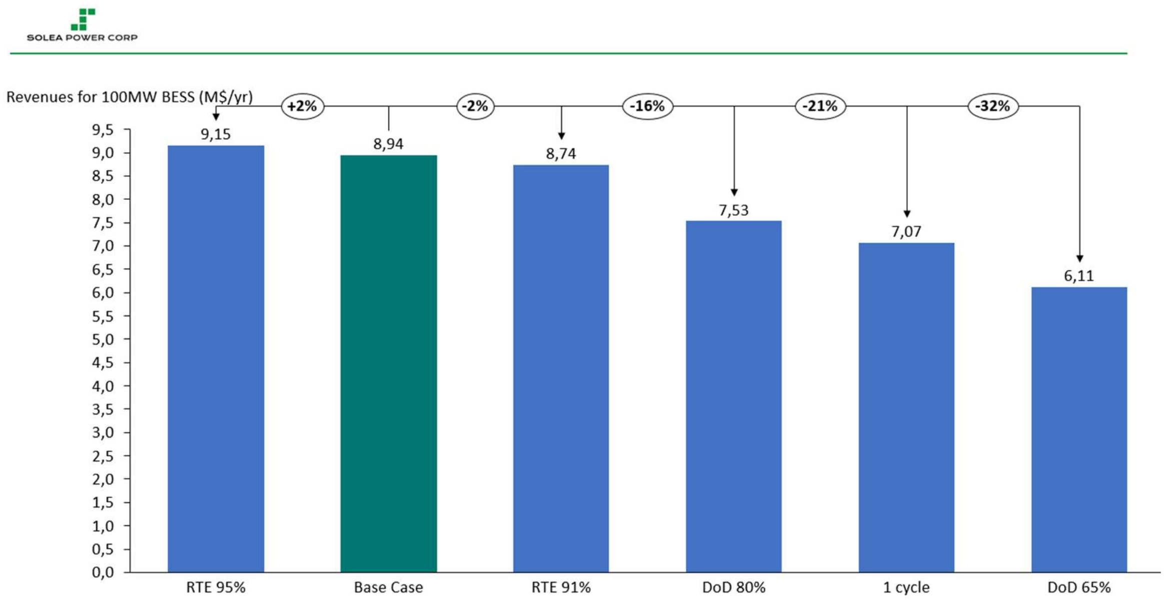


Figure 61. Revenue for Y1 per 100MW installation for different technical scenarios

4.3.4 Synthesis

This sensitivity analysis confirms that location and dispatch strategy are the decisive factors in ERCOT's BESS market. Dispatch tactics, CAPEX reductions and ITC support are necessary to lift projects from marginal to attractive status, while technical assumptions such as DoD and RTE provide fine-tuning rather than structural changes. In particular, the transition from DAM-only to DAM–RT dispatch represents the most powerful lever, capable of tripling shareholder IRR and halving payback times. The following table summarizes the sensitivity analysis, starting from the base case and working down from most to less impactful parameter changes.

Table 5. Sensitivity Analysis summary table

Scenario	Y1 Revenue ($)	Project IRR (%)	Shareholder IRR (%)	Project Payback (Years)
Base Case (DAM, 93% RTE, 95% DoD, Mid CAPEX of 756 $/kW)	8,941,265	4.93	6.0	10
DAM–RT Dispatch	14,682,303	16.12	31.7	5
Optimistic CAPEX (473 $/kW)	8,941,265	15.46	30.1	6
Conservative CAPEX (844 $/kW)	8,941,265	2.69	1.3	12
1 Cycle/Day	7,071,878	3.80	3.8	12
80% DoD	7,529,487	3.78	3.6	13
65% DoD	6,117,708	2.70	2.0	16
95% RTE	9,146,811	5.40	7.0	10
91% RTE	8,735,719	4.45	5.0	11

The sensitivity analysis highlights that market strategy and capital costs are the dominant levers of feasibility. Shifting from a DAM-only strategy to DAM–RT dispatch close to doubles annual revenues and raises project IRR above 16%, confirming the central role of real-time optimization for future models. Similarly, CAPEX assumptions critically shape outcomes: an optimistic cost trajectory brings IRRs to 15–30%, while conservative costs push the project close to unviability. By contrast, technical parameters such as DoD or round-trip efficiency affect results in smaller increments, extending or shortening asset life but not fundamentally altering feasibility.

5. CONCLUSIONS

Battery Energy Storage Systems (BESS) have emerged as one of the most critical technologies to ensure grid reliability and accelerate the energy transition. In ERCOT, where extreme volatility, renewable penetration, and the absence of a centralized capacity market create unique challenges, storage represents a clear pathway toward greater stability and efficiency in the grid. The market outlook is highly promising: cost declines, regulatory support such as the IRA, and continued investment in advanced chemistries and dispatch optimization all point toward accelerated growth in the coming decade, apart from the increase market participation from developers on BESS projects, and increase high demand growth that allows for higher BESS penetration with a lower risk associated to it.

At the same time, however, risks remain. Increasing competition in the ancillary services market close to full saturation, potential price cannibalization from oversupply of short-duration systems, and uncertainties around long-term policy design could affect the profitability of individual projects. These factors highlight that while the opportunity is significant, careful modeling and site-specific analysis remain essential to de-risk investment decisions, as done and analyzed in this thesis.

This thesis was motivated by two key drivers. First, the recognition that BESS has the potential to reshape ERCOT's market dynamics by reducing price volatility, mitigating curtailment, and enabling higher shares of renewable integration. Second, the strategic ambition to position Solea Power Corp. at the forefront of this transition by developing a robust business branch dedicated to storage projects, extending its existing well known solar development reputation. By creating a techno-economic model capable of capturing node-level revenues, this work seeks not only to quantify opportunity but also to provide a practical decision-support tool for developers, investors, and policymakers navigating ERCOT's rapidly evolving market.

5.1 METHODOLOGY REVIEW

The methodology developed in this thesis successfully integrated large-scale market data with a techno-economic modeling framework tailored to ERCOT's unique conditions. By combining SQL for data storage, Python for efficient extraction, and Excel with VBA for dispatch simulation and financial modeling, the system achieved both depth and accessibility. This hybrid design allowed complex nodal data from over 17,000 nodes to be processed while remaining usable for stakeholders without programming expertise.

$$ERCOT\ Data \rightarrow SQL \rightarrow Python \rightarrow Excel/VBA \rightarrow Results\ \&\ Financials$$

Key modeling assumptions, including conservative values for depth of discharge, round-trip efficiency, and system lifetime, were deliberately chosen, and contrasted with industry experts at the time, to reflect realistic project risk and functionality. The decision to simulate seasonal cycle strategies and incorporate degradation factors ensured the outputs were technically and financially accurate. At the same time, the use of node-level granularity provided a distinctive advantage, enabling project feasibility to be evaluated at a resolution rarely attempted in industry studies in this sector so far.

Nevertheless, several challenges emerged. The initial Excel CSV file processing speed limited scalability when compared to an SQL environment, having to add complexity to the model that directly translated into efficiency, going from a close to 1GB database to a 16GB database leading to this change to be necessary. In addition, the model excluded real-time trading and ancillary service participation in its base case, restricting revenue representation to DAM-DAM energy arbitrage only. While this was intentional to maintain analytical clarity, it highlights the need for more advanced dispatch approaches in future iterations. However, the real time trading combination with DAM energy purchase was also included later in the model to give an indicative measure of potential revenue growth.

5.2 Key Insights from Results

The analysis of ERCOT's nodal landscape showed that West Texas hubs remained the most profitable for energy arbitrage, with average revenues of nearly 90,500 $/MW-year, outperforming Houston (87,500 $/MW-year) and North (85,300 $/MW-year), hubs containing the two nodes analyzed in this thesis, Pamplona and Santa Monica. However, these gains are tempered by practical challenges, as West Texas is geographically remote, sparsely populated, and has a history of community resistance to new renewable projects. Houston, by contrast, faces tighter land availability and congestion, but its price volatility and higher average price levels still make it one of the most attractive regions for developers.

At the node level, the Pamplona project in Houston emerged as the most feasible of the studied cases, yielding close to 894,000 $ in Year 1 revenues for a 100 MW system, with a 10-year projected project payback. The Santa Monica project in the North Hub, while slightly less profitable, still highlighted the importance of solar pricing dynamics and co-location potential, showing that land-rich nodes with competitive solar pricing can still represent viable investment opportunities there, although this wasn't the main focus of the study.

Regarding co-location, results confirm that its value is secondary in low-curtailment hubs such as Houston and North. The real opportunity lies in West Texas, where solar generation frequently exceeds transmission capacity and curtailment levels are higher, especially due to the fact of high wind energy generation supported by Production Tax Credit, or PTC as mentioned earlier in this thesis. In such nodes, a BESS can meaningfully capture lost solar output and shift it to higher-priced hours, creating a dual benefit for project economics.

Finally, the study underscores the conditions under which BESS projects thrive or struggle. High-viability conditions include DAM-RT optimized dispatch and lower CAPEX scenarios, both of which can lift IRRs to investor-attractive levels above 15%. Conversely, conservative CAPEX, removal of the ITC, or restrictive operational parameters (e.g., shallow DoD, lower RTE) significantly erode feasibility, in some cases pushing IRRs below

3% and extending payback beyond acceptable ranges. This dual perspective illustrates the fine balance between market opportunity and financial risk in ERCOT's market.

5.3 LIMITATIONS OF THE STUDY

Like any techno-economic analysis, this study is built on a series of assumptions and simplifications that, while carefully chosen, inevitably introduce certain limitations to the whole scope of the study. These limitations reflect both the scope of the model design and the broader uncertainties that characterize ERCOT's evolving market environment. That being said, they should not be interpreted as flaws but rather as boundaries that frame the practical insights of this thesis, boundaries that could be developed in the future if a practical team can get behind this study.

At a technical level, the model deliberately excludes ancillary service participation, weather forecasting, and real-time dispatch adjustments. These were omitted to avoid overcomplicating the core structure and to maintain a clear focus on energy arbitrage, the most transparent and location-dependent revenue stream in ERCOT, also with the biggest growth to come in upcoming years. Assumptions such as fixed temperature operation (25°C), constant HVAC consumption (6%), and annualized degradation steps are simplifications that strike a balance between technical realism and computational and operational efficiency. While more granular modeling could capture marginal effects, the expected deviations in long-term outputs are minor compared to the broader trends highlighted by the model. On the data side, the study relies on March 2021 to September 2024 ERCOT DAM prices, as well as RT Hub prices outside the base case scenario. This window provides sufficient coverage of recent market dynamics, including the extreme summer of 2023, which saw very significant volatility. However, events such as Winter Storm Uri (Feb 2021) were excluded, as they represent rare outliers that would skew long-term feasibility assessments, even though as stated earlier in this thesis "almost payed off the CAPEX of the whole BESS project we had", stated by an industry expert. By focusing on "typical" high-volatility periods rather than one-off crises, the model produces results that are more representative of future project economics, rather than expecting that to happen within the project's lifetime.

Financial assumptions also carry inherent simplifications. OPEX was modeled as 3.5% (2.5% for maintenance and 1% for insurance) of CAPEX, with a fixed debt-to-equity structure and standardized tax brackets. While these reflect realistic averages from NREL and industry benchmarks, they do not account for project-specific variations such as site-specific insurance premiums. These exclusions were intentional, given that such details can be highly case-specific and would obscure the generalizable insights the thesis aims to deliver.

Ultimately, these limitations underline the purpose of the model: not to provide a deterministic forecast of project revenues, but to deliver an indicative framework for assessing the relative attractiveness of nodes across ERCOT. By focusing on arbitrage and scalable assumptions, the model serves as a decision-support tool that helps developers, investors, and policymakers to identify promising locations and understand the trade-offs involved in BESS deployment. Its results should therefore be read as directional guidance rather than exact predictions, highlighting where opportunity is most likely to materialize while acknowledging the inherent uncertainty of ERCOT's competitive market.

5.4 RECOMMENDATIONS FOR FUTURE WORK

The most immediate step forward lies in extending the current model from a DAM-only framework into a fully integrated DAM–RT dispatch tool. While this thesis has already demonstrated the theoretical upside of perfectly switching between DAM and RT's most profitable hours, this assumption represents an idealized scenario in which operators know future prices with certainty, which is technically impossible. The logical next phase, therefore, is to couple DAM–RT logic with predictive analytics, where machine learning or AI-based algorithms forecast nodal price movements based on patterns in demand, renewable generation, and system conditions, something that's been done before in several other markets and energy trading tactics. Even a moderately accurate predictive model could unlock significant additional value, transforming BESS operations from reactive to proactive and making BESS projects far more resilient to market volatility. Complementing this possibly, a probabilistic Monte Carlo modeling approach should be explored, although this should be treated as a phase II from future works. Monte Carlo would mean running thousands of dispatch scenarios under different stochastic inputs, where developers could not only refine the predictive model but also quantify the probability of achieving a certain revenue outcome under uncertainty. Such probabilistic insights would bridge the gap between theoretical optimization and bankable project risk assessments, directly supporting investment decision-making.

On a different note, despite signs of market saturation, the integration of ancillary services revenues remains a relevant lever. Products such as regulation up/down and, occasionally, ECRS, can provide valuable incremental revenues during specific system conditions, especially when energy arbitrage margins tighten at some point in time. Incorporating these services into the modeling framework would therefore broaden the spectrum of dispatch opportunities, ensuring BESS assets remain adaptable across changing market dynamics.

Another avenue for future refinement involves the integration of ERCOT's interconnection queue and transmission pipeline dynamically, and not statically as its integrated now. By automatically accounting for new projects under development, the model could anticipate localized congestion effects and revenue cannibalization risks from additional storage capacity. While complex, combining such a module with AI-driven DAM–RT dispatch would move the model closer to a full predictive model of ERCOT's evolving market landscape, capable of guiding real-world project siting and investment.

In conclusion, this thesis demonstrates that battery energy storage has a promising future in ERCOT. While challenges remain, ranging from volatility and market saturation to technological degradation, the upside is undeniable. By strategically deploying storage at the right nodes, optimizing dispatch between DAM and RT, and embracing predictive analytics, batteries can evolve from margin-dependent assets into cornerstone resources for both profitability and system stability. This is not only an opportunity for developers like Solea Power Corp., but also for the broader ERCOT grid, which increasingly relies on flexibility to integrate renewable energy generation and manage constant uncertainty, mainly due to extreme weather events and unexpected transmission system congestions. Importantly, the modeling framework presented here has already proven its practical value for Solea Power

Corp., enabling the company to streamline project evaluation by identifying viable nodes before committing to costly Screening and Full Interconnection Studies. By reducing both working hours and upfront costs, the model has become a critical decision-support tool for a startup with ambitious stakeholders seeking to maximize impact with limited resources. Ultimately, the work presented here is both a reflection of current possibilities and a call to action, as the models built today will shape not only the projects of tomorrow but also the strategic pathways of companies driving the energy transition forward.

BIBLIOGRAPHY

- ERCOT. (2023). *Market operations and nodal pricing documentation*. Electric Reliability Council of Texas. https://www.ercot.com
- Grimaldi, A., Minuto, F. D., Perol, A., Casagrande, S., & Lanzini, A. (2023). 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*, 65, 107232. https://doi.org/10.1016/j.est.2023.107232
- International Energy Agency. (2024). *Global Energy Storage Report 2024*. https://www.iea.org/reports/global-energy-storage
- NREL. (2023). *2023 Battery Storage Cost Projections and Market Trends*. National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy23osti/82319.pdf
- Timmermans, J. M., Nikolian, A., De Hoog, J., Gopalakrishnan, R., Goutam, S., Omar, N., Coosemans, T., & Van Mierlo, J. (2016). Batteries 2020 – Lithium-ion battery first and second life ageing, validated battery models, lifetime modelling and ageing assessment of thermal parameters. In *2016 18th European Conference on Power Electronics and Applications (EPE'16 ECCE Europe)*. IEEE. https://doi.org/10.1109/EPE.2016.7695698
- U.S. Energy Information Administration. (2024). *Electric Power Monthly: Texas renewable generation*. https://www.eia.gov/electricity/monthly/
- S&P Global. (2024, April 10). *US renewables tracker: ERCOT back on top in Q1 for total renewable generation output*. https://www.spglobal.com/commodityinsights/en/market-insights/latest-news/electric-power/041024-us-renewables-tracker-ercot-back-on-top-in-q1-for-total-renewable-generation-output
- International Energy Agency. (2022). *Executive summary – Batteries and secure energy transitions*. https://www.iea.org/reports/batteries-and-secure-energy-transitions/executive-summary
- Fu, R., Margolis, R., & Woodhouse, M. (2019). *Economic analysis of battery energy storage systems (NREL/TP-6A20-74426). National Renewable Energy Laboratory*. https://www.nrel.gov/docs/fy19osti/74426.pdf

- TESLA Group a.s. (2023). *How do BESS work – Complete guide.* https://www.teslagroup.eu/insights/how-do-bess-work-complete-guide/
- National Renewable Energy Laboratory. (2024). *Utility-scale battery storage – 2024 Annual Technology Baseline (ATB).* https://atb.nrel.gov/electricity/2024/index
- Liu, Y., Wang, Y., Wen, M., Chen, Y., Wang, X., & Lu, D. (2020). *Multi-objective optimization of hybrid energy systems under different dispatch strategies using a novel improved grey wolf optimizer*. Energy Conversion and Management, 224, 113270. https://doi.org/10.1016/j.enconman.2020.113270
- Ossila. (n.d.). *Lithium-ion batteries: Overview, chemistry, advantages & disadvantages*. Ossila. https://www.ossila.com/pages/lithium-ion-batteries
- Federal Emergency Management Agency. (2023, May 25). *Emerging hazards: Battery energy storage system fires*. U.S. Department of Homeland Security. https://www.fema.gov/case-study/emerging-hazards-battery-energy-storage-system-fires
- Modo Energy. (2024, February 2). *ERCOT BESS Index: Battery revenues in 2023 surpass $1.2bn — new ECRS service shakes up market*. https://modoenergy.com/research/ercot-battery-energy-storage-systems-annual-revenues-2023-bess-index-ancillary-services-arbitrage-ecrs
- Modo Energy. (2023, August 4). *Texas BESS Leaderboard H1 2023: ERCOT battery revenues total $717m*. https://modoenergy.com/research/ercot-battery-energy-storage-systems-revenues-january-june-2023-leaderboard
- Modo Energy. (2024, March 14). *How ERCOT BESSs use Day-Ahead and Real-Time prices to maximize revenue*. https://modoenergy.com/research/ercot-dart-optimization-explainer-day-ahead-real-time-trading-dart-spread-settlement-energy-arbitrage-battery-energy-storage
- U.S. Energy Information Administration. (2021, July 26). *Winter storm affected Texas energy prices and demand*. https://www.eia.gov/todayinenergy/detail.php?id=47876
- BCC Research. (2024, December 9). *Flow batteries: The future of energy storage.* https://blog.bccresearch.com/flow-batteries-the-future-of-energy-storage
- Infinite Power. (2024, December 25). *What are liquid flow batteries and their advantages?* https://www.infinitepowerht.com/what-are-liquid-flow-batteries-and-their-advantages.html
- (2025, August 1). *ERCOT BESS Outlook Q2 2025: Battery business case and investment outlook*. Modo Energy. https://modoenergy.com/research/ercot-bess-outlook-q2-2025-

battery-energy-storage-system-business-case-investment-forecast-capex-irr-returns-costs-risk-potential-texas-us-1h-2h-revenue

- U.S. Energy Information Administration. (2021, July 26). *Winter storm affected Texas energy prices and demand*. https://www.eia.gov/todayinenergy/detail.php?id=47876

DOCUMENT 2. ANNEX

ANNEX I: ALIGNMENT WITH THE SUSTAINABLE DEVELOPMENT GOALS (SDGS)

The optimization of BESS projects and dispatch strategies in the ERCOT market aligns with several key Sustainable Development Goals (SDGs) established by the United Nations. By enhancing energy storage efficiency and supporting a more resilient and sustainable power grid, this project contributes to global sustainability efforts in the following ways:

SDG 7: Affordable and Clean Energy – The project directly addresses the need for reliable, clean, and affordable energy by optimizing the economic viability of battery storage systems. By facilitating the integration of renewable energy sources such as wind and solar, BESS reduces curtailment and ensures that clean electricity is available even during periods of low generation. This improves grid stability and promotes a more sustainable energy mix.

SDG 9: Industry, Innovation, and Infrastructure – The increasing adoption of battery storage in ERCOT represents a shift in energy infrastructure, enabling a smarter and more flexible grid. The project contributes to technological innovation by developing a techno-economic model that enhances decision-making for BESS deployment. This supports investment in resilient energy infrastructure, fostering long-term sustainability in the power sector.

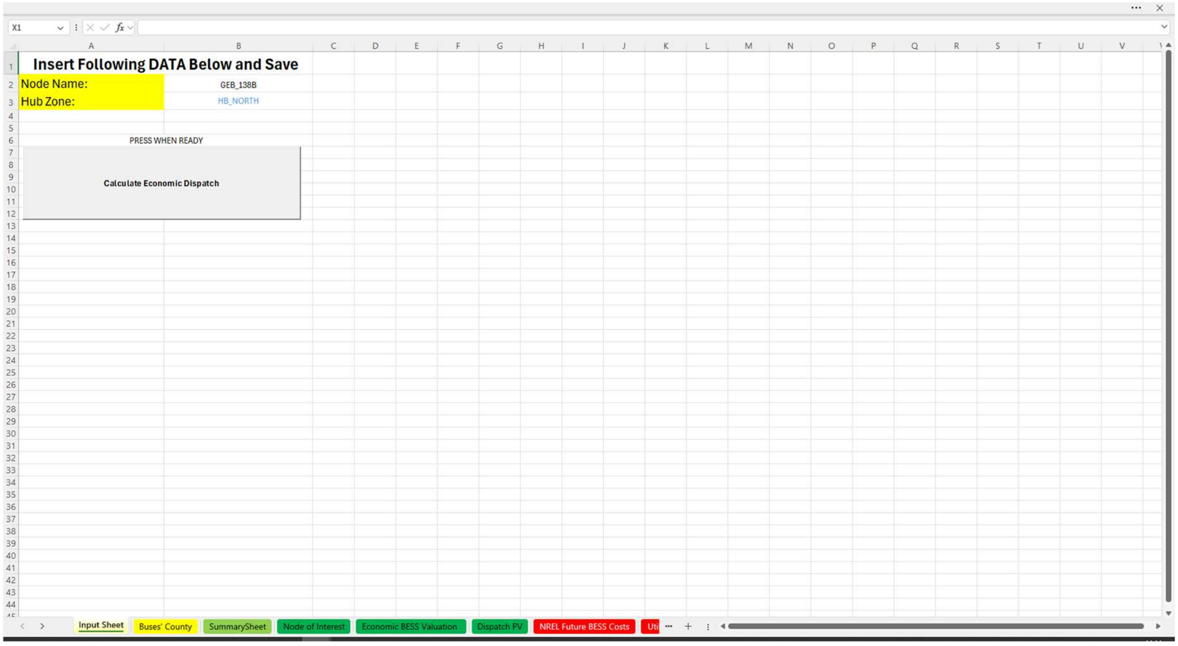
SDG 11: Sustainable Cities and Communities – A more stable and efficient electricity grid leads to reduced power outages and greater energy reliability, benefiting urban and rural communities alike. By improving the ability to store and dispatch electricity efficiently, the project helps mitigate the effects of energy shortages, which is particularly relevant in extreme weather events such as those experienced in Texas in recent years.

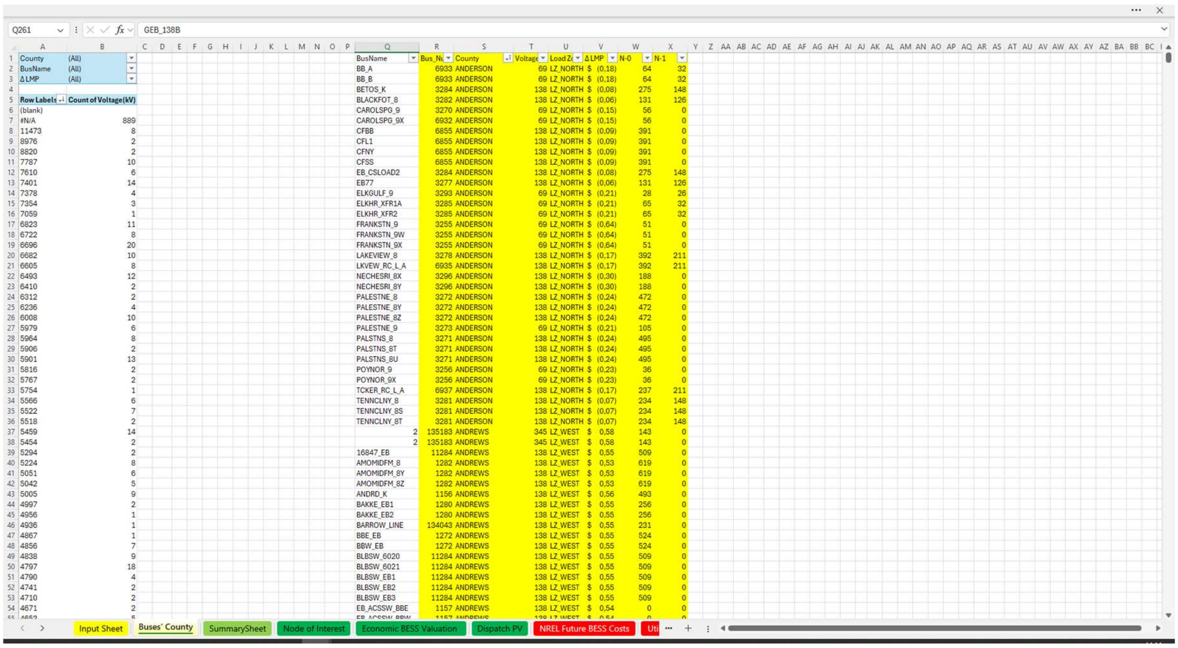
SDG 12: Responsible Consumption and Production – The project promotes efficient energy use by optimizing battery charging and discharging cycles to minimize waste. By leveraging data-driven strategies, it ensures that energy is used more effectively, reducing reliance on inefficient fossil-fuel-based peaker plants and decreasing overall energy losses in the system.

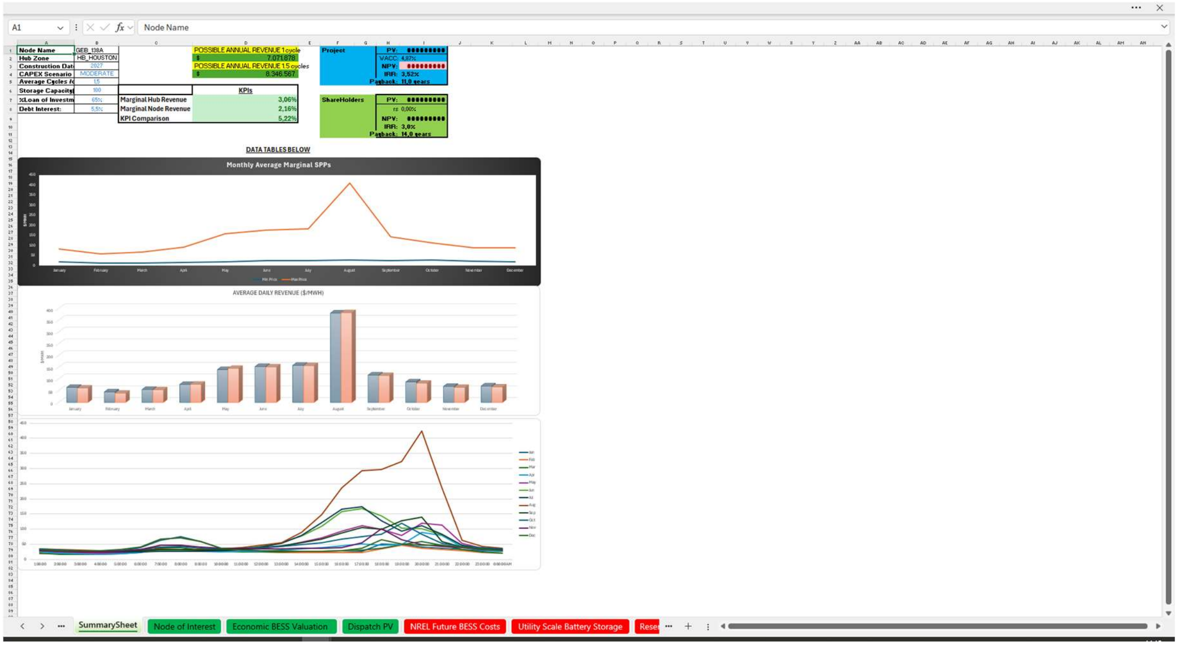
SDG 13: Climate Action – The role of battery storage in reducing greenhouse gas emissions is fundamental to combating climate change. By enabling better utilization of renewable energy and decreasing dependence on carbon-intensive backup power generation, this project contributes to lowering the grid's carbon footprint. Furthermore, by optimizing dispatch strategies, it helps reduce market volatility and the need for expensive, high-emission power generation during peak hours.

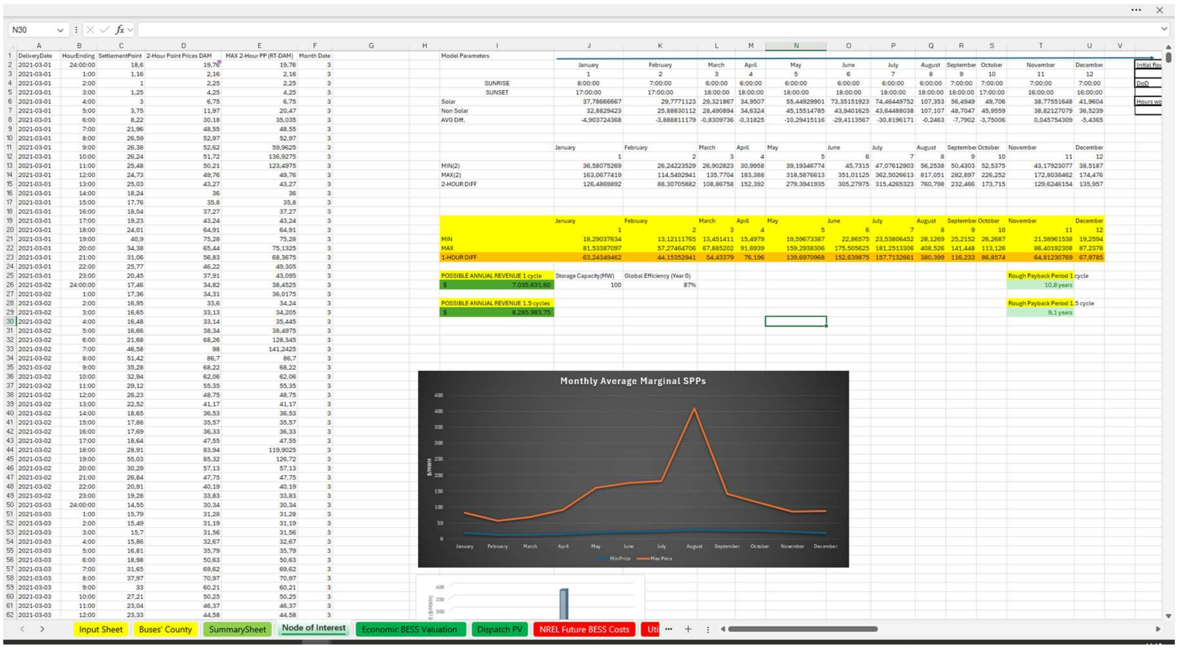
Through these contributions, the project not only advances the energy transition within ERCOT but also serves as a model for sustainable energy development in deregulated electricity markets worldwide.

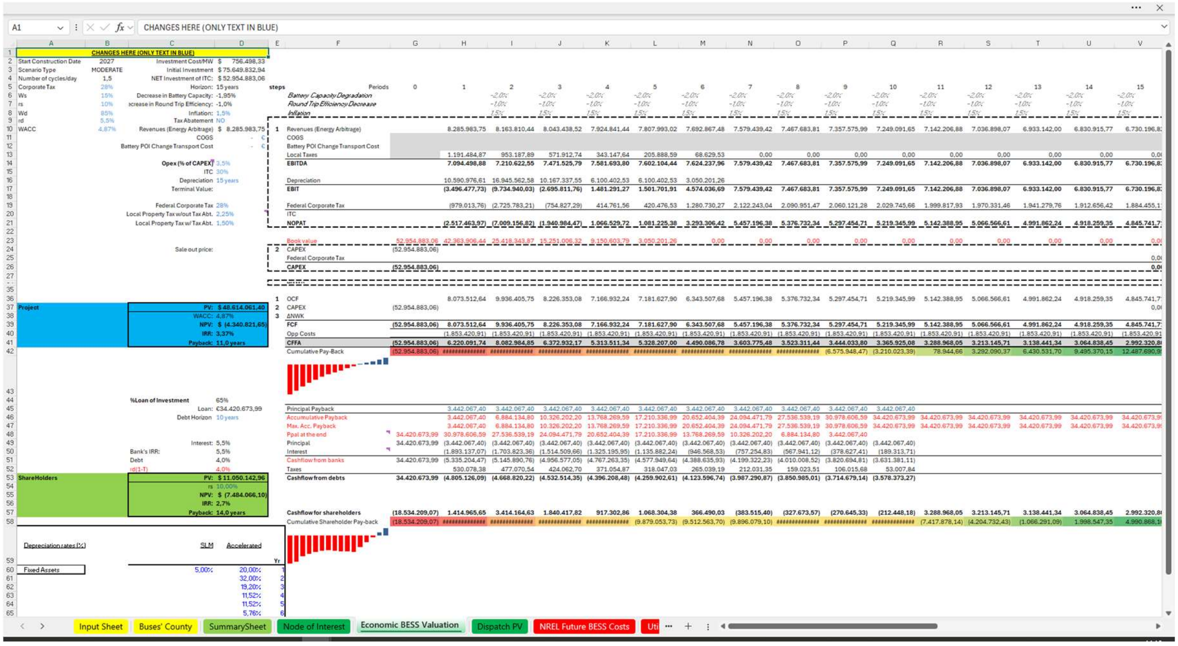
ANNEX II: 2-HOUR BATTERY VALUATION BESS BASE MODEL

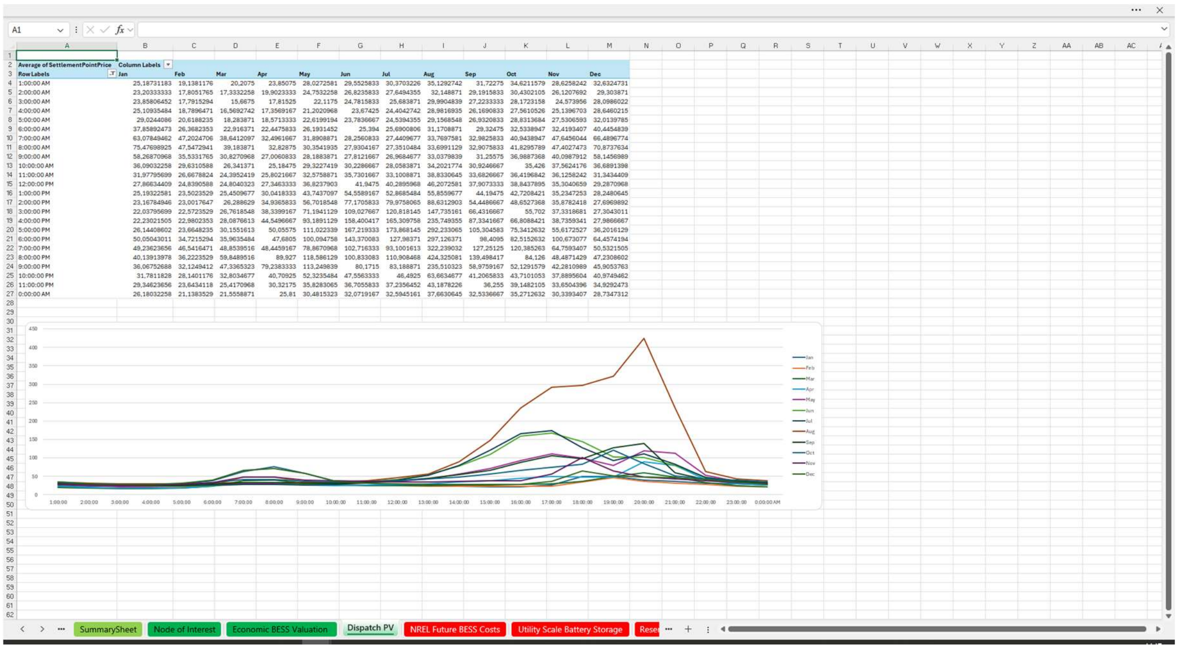


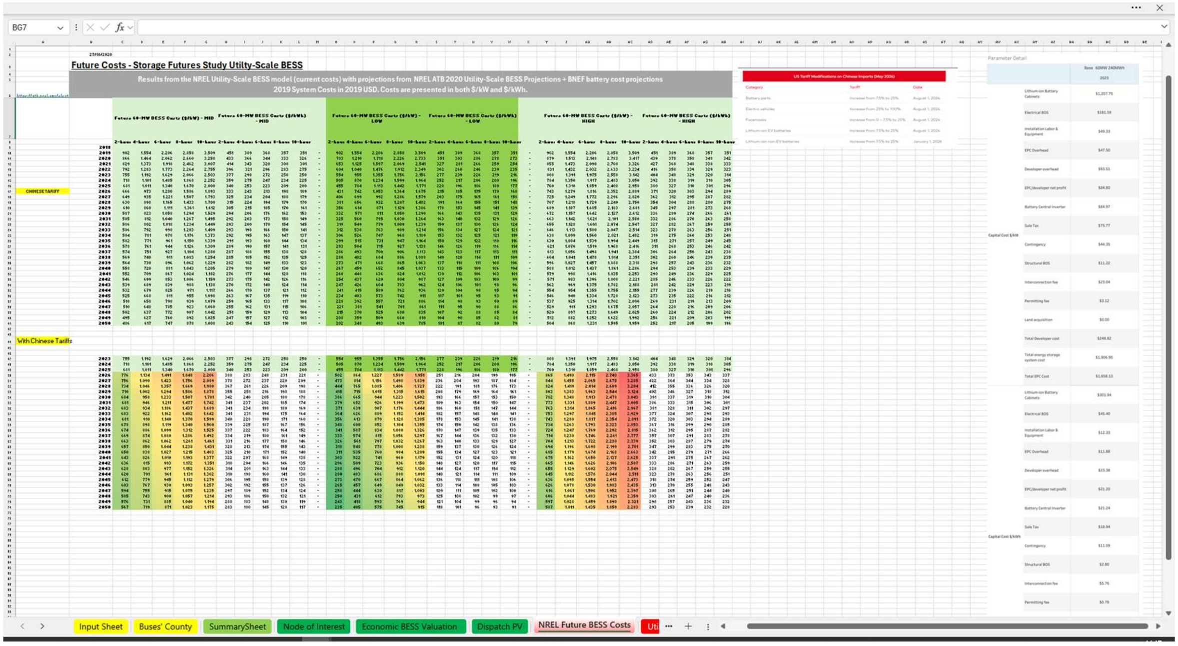


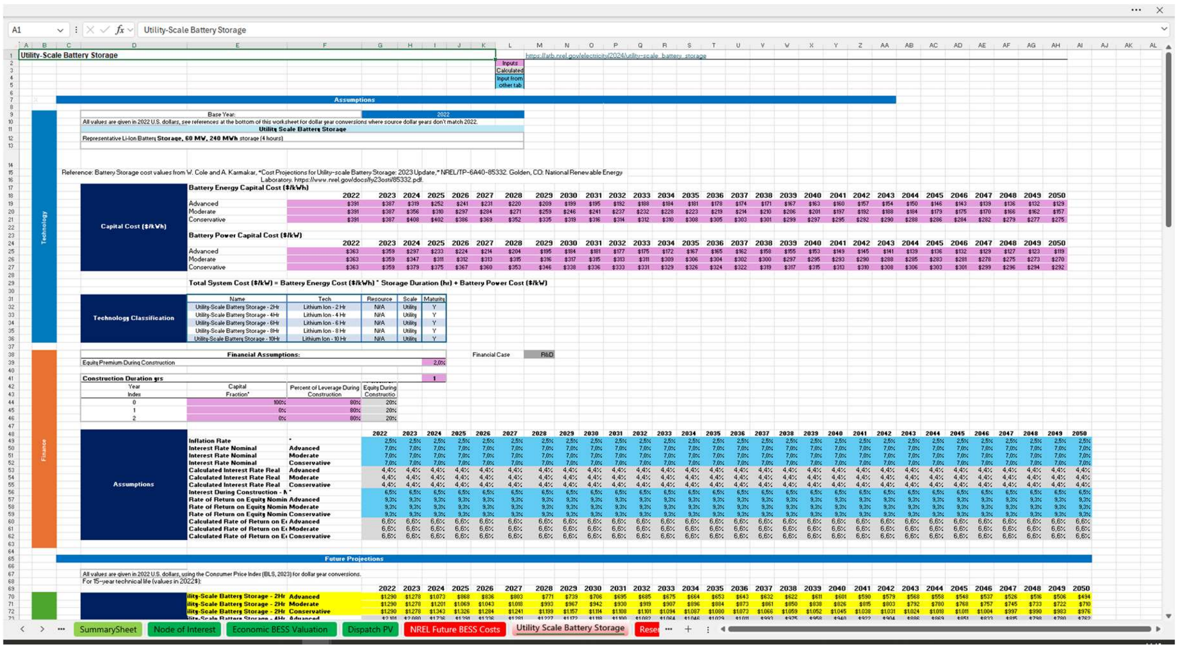





CHANGES HERE (ONLY TEXT IN BLUE)
Input Sheet
Buses' County
SummarySheet
Node of Interest
Economic BESS Valuation
Dispatch PV
NREL Future BESS Costs


SummarySheet
Node of Interest
Economic BESS Valuation
Dispatch PV
NREL Future BESS Costs
Utility Scale Battery Storage


Future Costs - Storage Futures Study Utility-Scale BESS
Input Sheet
Buses' County
SummarySheet
Node of Interest
Economic BESS Valuation
Dispatch PV
NREL Future BESS Costs

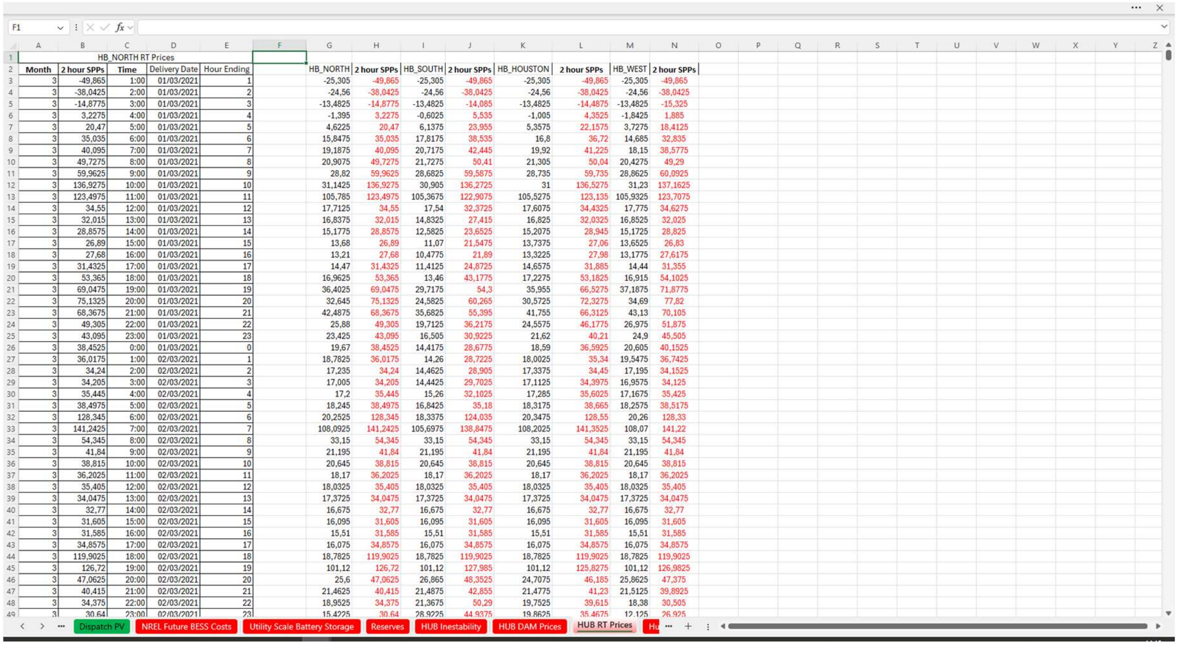

Utility-Scale Battery Storage
Assumptions
Capital Cost ($/kWh)
Technology Classification
Financial Assumptions:
Future Projections
SummarySheet
Node of Interest
Economic BESS Valuation
Dispatch PV
NREL Future BESS Costs
Utility Scale Battery Storage

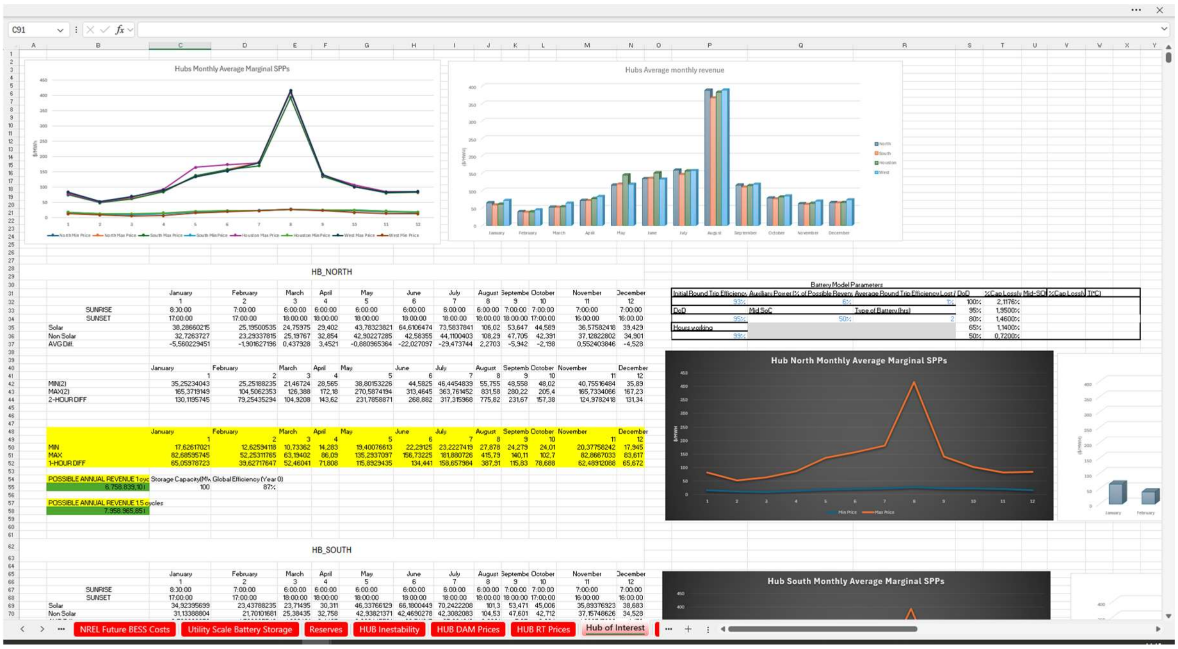
DeliveryDate	HourEndir	REGUP	2-Hour REGUP	REGDOWN	2-Hour REGDOWN	RRS	2-Hour RRS	NSRS	2-Hour NSRS	ECRS	2-Hour ECRS
24/06/2021	1:00	4,73	7,73	15	23	4,43	8,58	0,49	0,98		0
24/06/2021	2:00	3	7,73	8	23	4,15	8,58	0,49	0,98		0
24/06/2021	3:00	3	6	7,21	15,21	4,15	8,3	0,57	1,06		0
24/06/2021	4:00	4	7	4,27	11,48	4,15	8,3	0,57	1,14		0
24/06/2021	5:00	4	8	4	8,27	4,21	8,36	0,57	1,14		0
24/06/2021	6:00	4,3	8,3	7,21	11,21	4,21	8,42	0,58	1,15		0
24/06/2021	7:00	5,1	9,4	4,03	11,24	4,5	8,71	3	3,58		0
24/06/2021	8:00	5	10,1	4,63	8,66	5	9,5	3,66	6,66		0
24/06/2021	9:00	5,3	10,3	7,99	12,62	5	10	3,73	7,39		0
24/06/2021	10:00	9,47	14,77	9,46	17,45	9,46	14,46	4	7,73		0
24/06/2021	11:00	10,99	20,46	5	14,46	10,99	20,45	2,58	6,58		0
24/06/2021	12:00	15,97	26,96	0,76	5,76	15,98	26,97	2,58	5,16		0
24/06/2021	13:00	13,33	29,3	0,98	1,74	15,73	31,71	1,5	4,08		0
24/06/2021	14:00	20,57	33,9	9,32	10,3	22,72	38,45	4,57	6,07		0
24/06/2021	15:00	29,54	50,11	4,02	13,34	34	56,72	8	12,57		0
24/06/2021	16:00	42	71,54	6,71	10,73	48	82	8	16		0
24/06/2021	17:00	36,15	78,15	8,79	15,5	47,66	95,66	7,25	15,25		0
24/06/2021	18:00	26,19	62,34	4	12,79	27,94	75,6	8	15,25		0
24/06/2021	19:00	14,7	40,89	5	9	15,72	43,66	1,15	9,15		0
24/06/2021	20:00	12,3	27	4	9	13,84	29,56	0,98	2,13		0
24/06/2021	21:00	7,1	19,4	4	8	8,47	22,31	0,96	1,94		0
24/06/2021	22:00	7,55	14,65	7,21	11,21	8,52	16,99	0,74	1,7		0
24/06/2021	23:00	9,11	16,66	11,4	18,61	10	18,52	0,48	1,22		0
24/06/2021	24:00:00	7,76	16,87	12	23,4	8,02	18,02	0,38	0,86		0
25/06/2021	1:00	12,45	20,21	16,56	28,56	5,06	13,08	0,58	0,96		0
25/06/2021	2:00	5	17,45	7,01	23,57	4,2	9,26	0,58	1,16		0
25/06/2021	3:00	3,8	8,8	6	13,01	3,5	7,7	0,94	1,52		0
25/06/2021	4:00	4	7,8	4,58	10,58	3,5	7	0,94	1,88		0
25/06/2021	5:00	4,45	8,45	4	8,58	4,15	7,65	0,94	1,88		0
25/06/2021	6:00	6,45	10,9	4	8	4,21	8,36	0,94	1,88		0
25/06/2021	7:00	6,95	13,4	5	9	6,15	10,36	5,85	6,79		0
25/06/2021	8:00	6,75	13,7	5	10	6,15	12,3	5,95	11,8		0
25/06/2021	9:00	10	16,75	8	13	9,15	15,3	8	13,95		0
25/06/2021	10:00	23,5	33,5	15	23	9,15	18,3	8	16		0
25/06/2021	11:00	14,03	37,53	6,86	21,86	13,23	22,38	2,58	10,58		0
25/06/2021	12:00	16,85	30,88	0,02	6,88	16,45	29,68	2,58	5,16		0
25/06/2021	13:00	17,3	34,15	0,35	0,37	18	34,45	2,58	5,16		0
25/06/2021	14:00	17,6	34,9	19,62	19,97	19,62	37,62	4,55	7,13		0
25/06/2021	15:00	29,54	47,14	3,17	22,79	34	53,62	12	16,55		0
25/06/2021	16:00	33,39	62,93	5,4	8,57	40	74	15	27		0
25/06/2021	17:00	38,22	71,61	6,69	12,09	45,22	85,22	17	32		0
25/06/2021	18:00	18,79	57,01	8,06	14,75	24,42	69,64	8	25		0
25/06/2021	19:00	14,71	33,5	15,35	23,41	15,35	39,77	1,1	9,1		0
25/06/2021	20:00	8	22,71	13,99	29,34	14,07	29,42	1,29	2,39		0
25/06/2021	21:00	5	13	6	19,99	8	22,07	0,97	2,26		0
25/06/2021	22:00	8,02	13,02	8,16	14,16	8,16	16,16	0,96	1,93		0
25/06/2021	23:00	6,82	14,84	40	48,16	9,68	17,84	0,94	1,9		0
25/06/2021	24:00:00	3,71	10,53	12	52	6	15,68	0,85	1,79		0

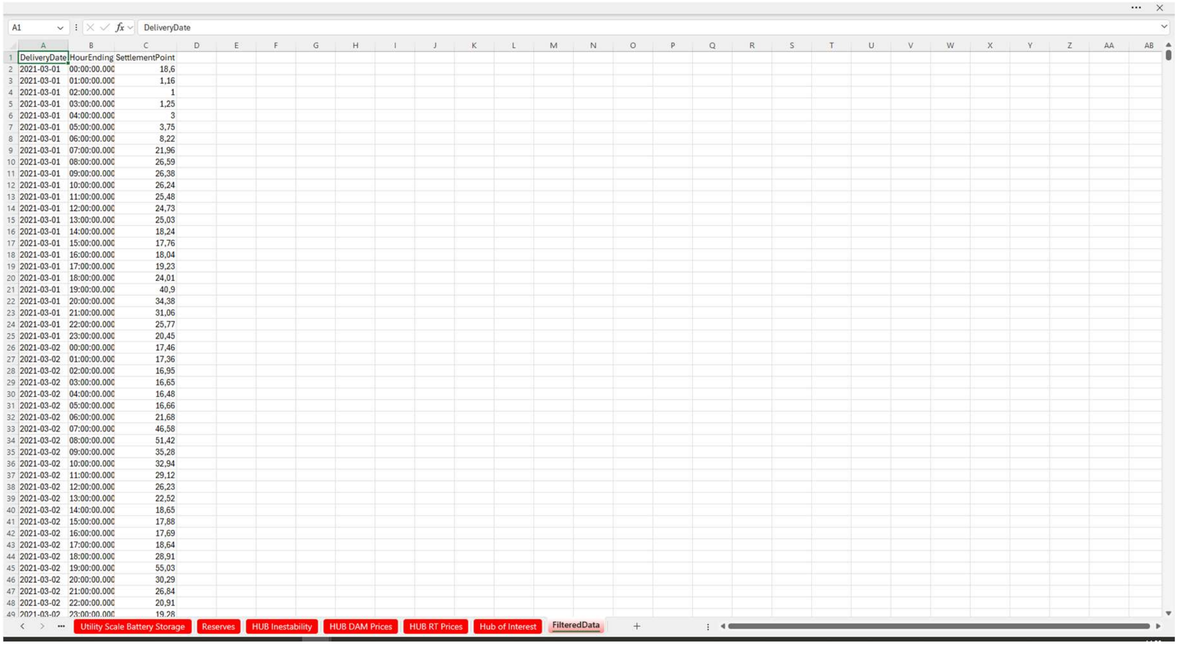
Node of Interest | Economic BESS Valuation | Dispatch PV | NREL Future BESS Costs | Utility Scale Battery Storage | Reserves | HUB Inestal

DeliveryDate	HourEnding	HB_NORTH	HB_SOUTH	HB_HOUSTON	HB_WEST	HB_BUSAVG
01/03/2021	1:00	1,16	1,16	1,16	0,97	1,14
01/03/2021	2:00	1	0,99	1	0,94	0,99
01/03/2021	3:00	1,25	1,25	1,25	1,25	1,25
01/03/2021	4:00	3	3	3	2,99	3
01/03/2021	5:00	3,75	3,75	3,75	3,75	3,75
01/03/2021	6:00	8,21	8,23	8,22	8,2	8,21
01/03/2021	7:00	21,88	21,92	21,97	21,58	21,87
01/03/2021	8:00	26,57	26,6	26,59	26,58	26,58
01/03/2021	9:00	26,35	26,38	26,37	26,36	26,36
01/03/2021	10:00	26,26	26	26,52	26,18	26,23
01/03/2021	11:00	25,51	25,09	25,91	25,41	25,46
01/03/2021	12:00	24,78	23,97	25,6	24,62	24,7
01/03/2021	13:00	25,04	23,52	26,52	24,77	24,88
01/03/2021	14:00	18,03	16,63	19,21	17,82	17,87
01/03/2021	15:00	17,55	15,92	18,66	17,36	17,33
01/03/2021	16:00	17,86	15,55	18,92	17,69	17,49
01/03/2021	17:00	18,95	16,22	19,82	18,83	18,46
01/03/2021	18:00	23,74	20,11	24,9	23,58	23,09
01/03/2021	19:00	40,84	36,38	42,11	40,77	40,04
01/03/2021	20:00	34,36	29,88	35,45	34,27	33,53
01/03/2021	21:00	31,19	27,16	31,92	31,1	30,4
01/03/2021	22:00	25,81	22,44	26,08	25,89	25,12
01/03/2021	23:00	20,38	17,13	20,22	20,62	19,67
01/03/2021	24:00:00	18,63	15,28	18,68	18,81	17,92
02/03/2021	1:00	17,6	14,13	17,02	18,02	16,81
02/03/2021	2:00	17,09	13,56	16,51	17,46	16,27
02/03/2021	3:00	16,82	13,45	16,31	17,16	16,05
02/03/2021	4:00	16,67	13,28	16,1	17,02	15,88
02/03/2021	5:00	16,9	13,62	16,36	17,29	16,15
02/03/2021	6:00	22,15	18,1	21,95	22,63	21,29
02/03/2021	7:00	47,05	41,78	47	47,57	45,95
02/03/2021	8:00	51,84	46,1	51,82	52,28	50,64
02/03/2021	9:00	35,5	31,81	35,77	35,29	34,71
02/03/2021	10:00	32,88	30,11	33,89	32,49	32,37
02/03/2021	11:00	29,11	28,04	29,93	28,72	28,95
02/03/2021	12:00	26,25	25,99	26,46	26,02	26,19
02/03/2021	13:00	22,56	22,11	22,68	22,02	22,42
02/03/2021	14:00	18,7	18,6	18,66	18,21	18,62
02/03/2021	15:00	17,91	17,86	17,88	17,54	17,85
02/03/2021	16:00	17,73	17,65	17,69	17,2	17,65
02/03/2021	17:00	18,63	18,48	18,61	18,18	18,54
02/03/2021	18:00	28,91	28,77	28,89	28,45	28,82
02/03/2021	19:00	55	54,93	55,01	55	54,99
02/03/2021	20:00	30,25	30,17	30,27	30,25	30,24
02/03/2021	21:00	26,8	26,72	26,82	26,8	26,79
02/03/2021	22:00	20,87	20,77	20,89	20,72	20,83
02/03/2021	23:00	19,39	19,8	19,26	19,4	19,46
02/03/2021	24:00:00	17,43	17,49	17,46	17,4	17,44

Dispatch PV | NREL Future BESS Costs | Utility Scale Battery Storage | Reserves | HUB Inestability | HUB DAM Prices | HUB RT Prices

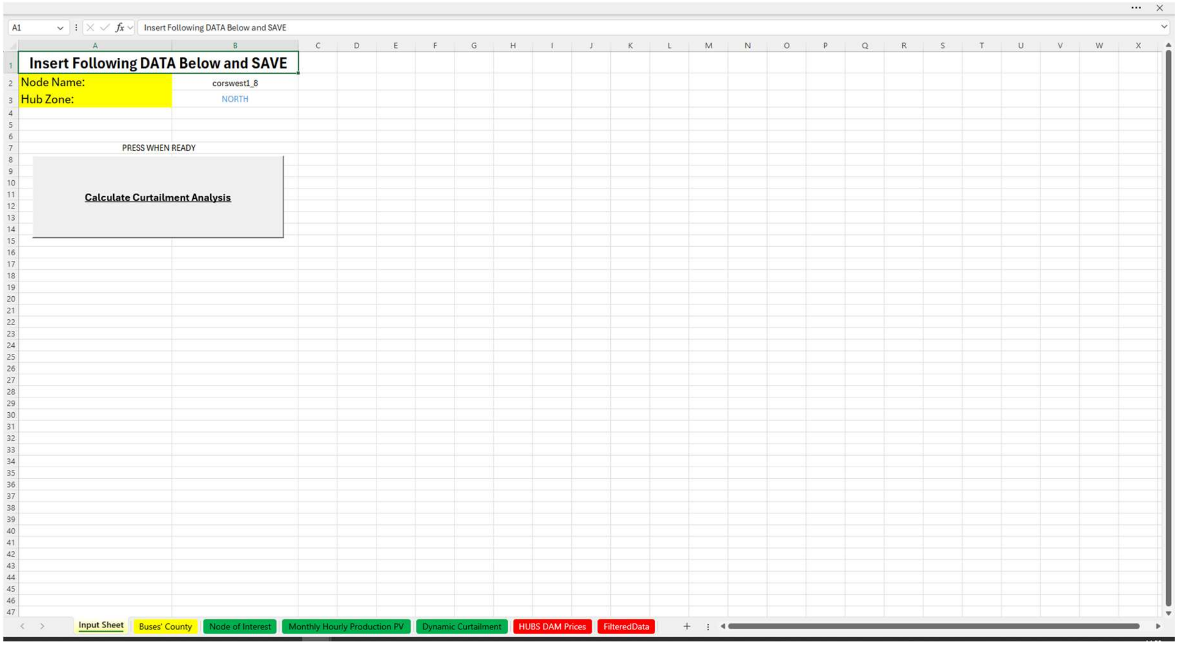

HB_NORTH RT Prices
Month
2 hour SPPs
Time
Delivery Date
Hour Ending
HB_NORTH
HB_SOUTH
HB_HOUSTON
HB_WEST
Dispatch PV
NREL Future BESS Costs
Utility Scale Battery Storage
Reserves
HUB Instability
HUB DAM Prices
HUB RT Prices

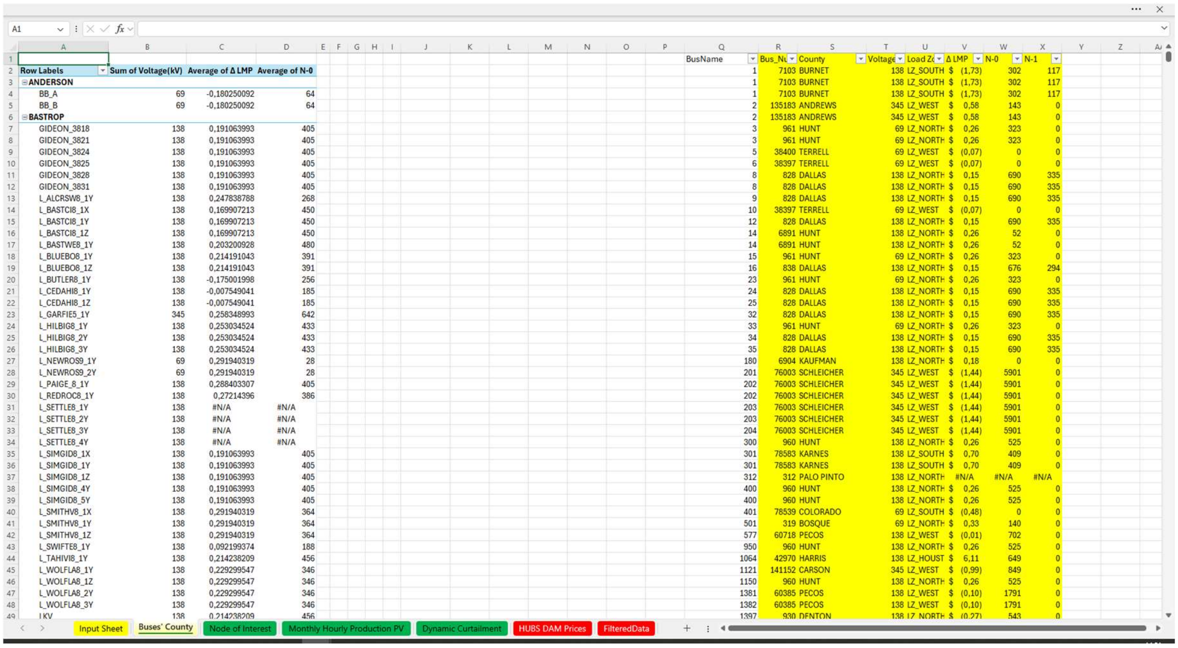

Hubs Monthly Average Marginal SPPs
Hubs Average monthly revenue
HB_NORTH
Hub North Monthly Average Marginal SPPs
HB_SOUTH
Hub South Monthly Average Marginal SPPs
NREL Future BESS Costs
Utility Scale Battery Storage
Reserves
HUB Instability
HUB DAM Prices
HUB RT Prices
Hub of Interest

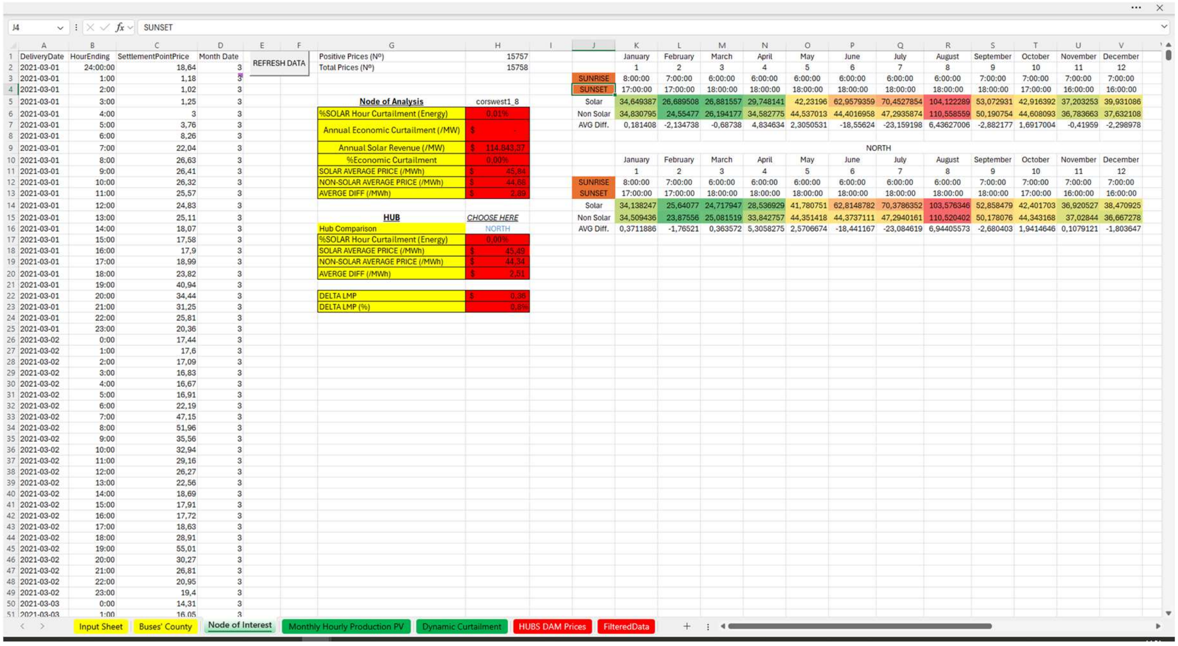


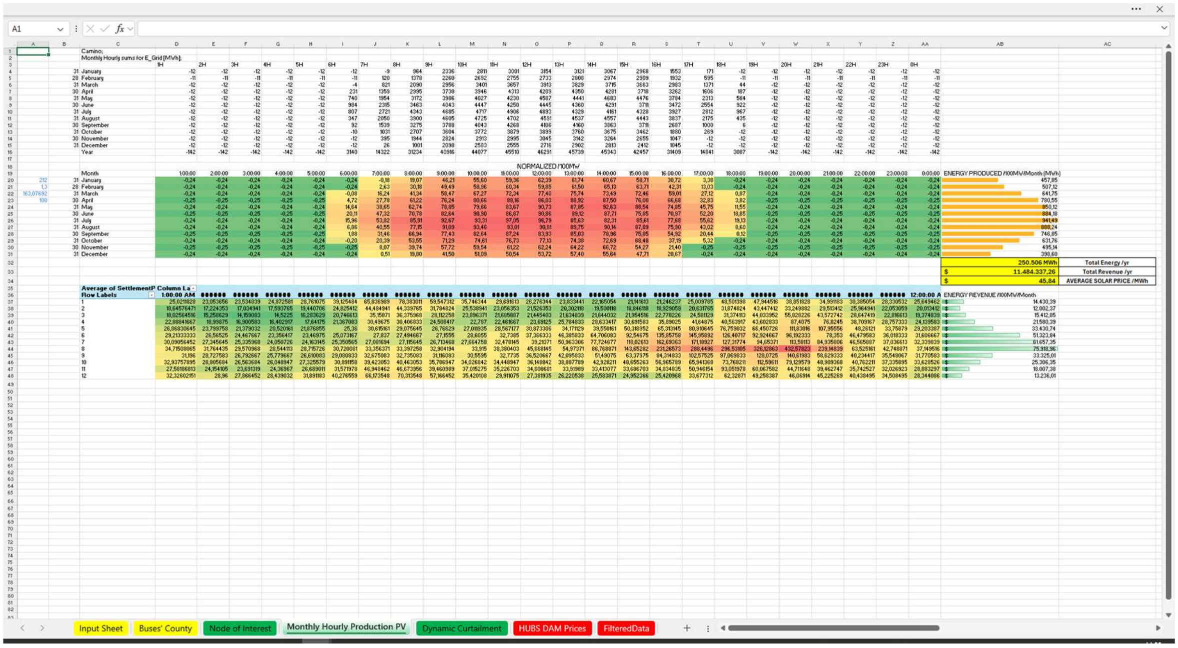
	A	B	C
1	DeliveryDate	HourEnding	SettlementPoint
2	2021-03-01	00:00:00.000	18,6
3	2021-03-01	01:00:00.000	1,16
4	2021-03-01	02:00:00.000	1
5	2021-03-01	03:00:00.000	1,25
6	2021-03-01	04:00:00.000	3
7	2021-03-01	05:00:00.000	3,75
8	2021-03-01	06:00:00.000	8,22
9	2021-03-01	07:00:00.000	21,96
10	2021-03-01	08:00:00.000	26,59
11	2021-03-01	09:00:00.000	26,38
12	2021-03-01	10:00:00.000	26,24
13	2021-03-01	11:00:00.000	25,48
14	2021-03-01	12:00:00.000	24,73
15	2021-03-01	13:00:00.000	25,03
16	2021-03-01	14:00:00.000	18,24
17	2021-03-01	15:00:00.000	17,76
18	2021-03-01	16:00:00.000	18,04
19	2021-03-01	17:00:00.000	19,23
20	2021-03-01	18:00:00.000	24,01
21	2021-03-01	19:00:00.000	40,9
22	2021-03-01	20:00:00.000	34,38
23	2021-03-01	21:00:00.000	31,06
24	2021-03-01	22:00:00.000	25,77
25	2021-03-01	23:00:00.000	20,45
26	2021-03-02	00:00:00.000	17,46
27	2021-03-02	01:00:00.000	17,36
28	2021-03-02	02:00:00.000	16,95
29	2021-03-02	03:00:00.000	16,65
30	2021-03-02	04:00:00.000	16,48
31	2021-03-02	05:00:00.000	16,66
32	2021-03-02	06:00:00.000	21,68
33	2021-03-02	07:00:00.000	46,58
34	2021-03-02	08:00:00.000	51,42
35	2021-03-02	09:00:00.000	35,28
36	2021-03-02	10:00:00.000	32,94
37	2021-03-02	11:00:00.000	29,12
38	2021-03-02	12:00:00.000	26,23
39	2021-03-02	13:00:00.000	22,52
40	2021-03-02	14:00:00.000	18,65
41	2021-03-02	15:00:00.000	17,88
42	2021-03-02	16:00:00.000	17,69
43	2021-03-02	17:00:00.000	18,64
44	2021-03-02	18:00:00.000	28,91
45	2021-03-02	19:00:00.000	55,03
46	2021-03-02	20:00:00.000	30,29
47	2021-03-02	21:00:00.000	26,84
48	2021-03-02	22:00:00.000	20,91
49	2021-03-02	23:00:00.000	19,28

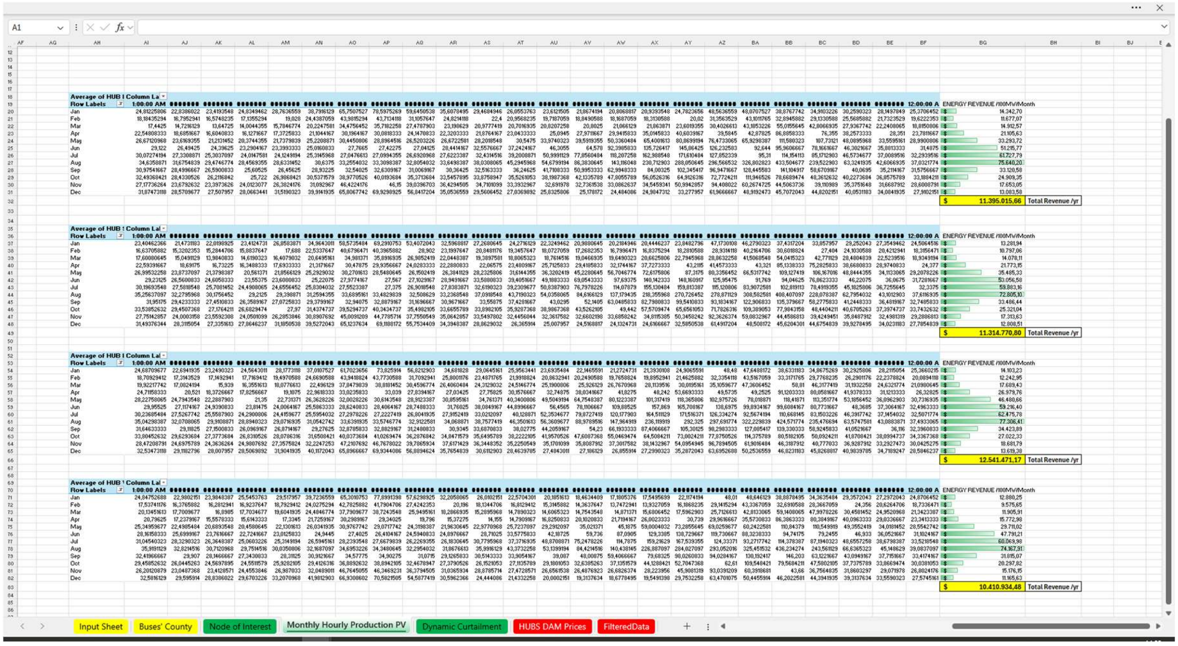
ANNEX III: CURTAILMENT ANALYSIS BASE MODEL

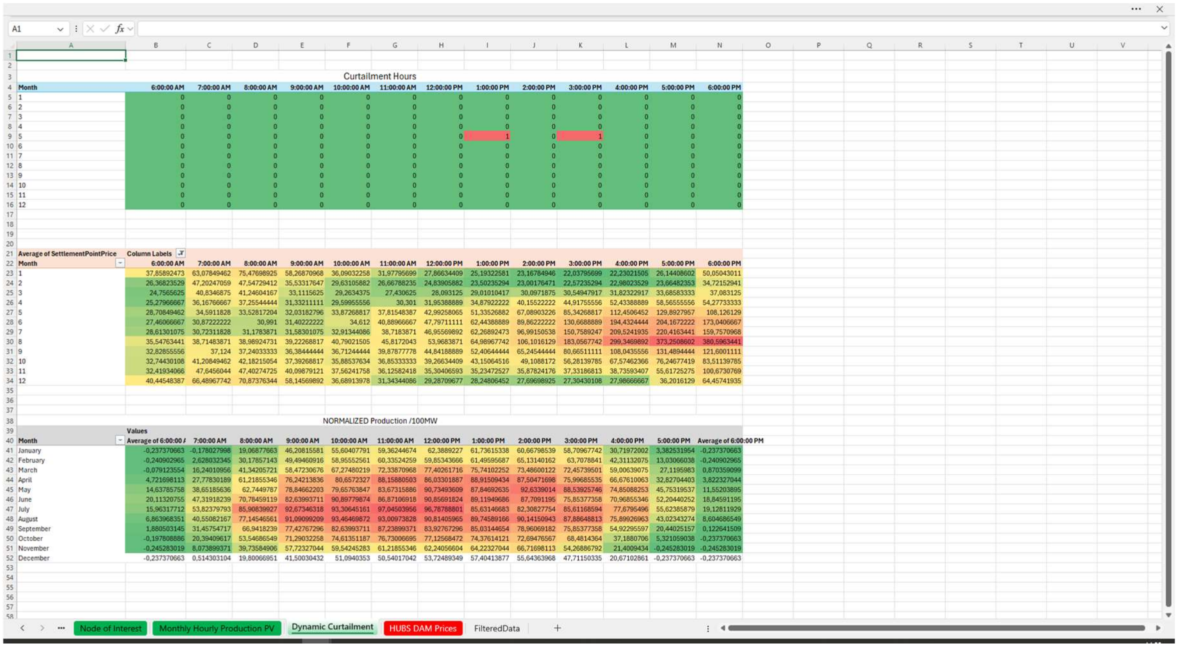


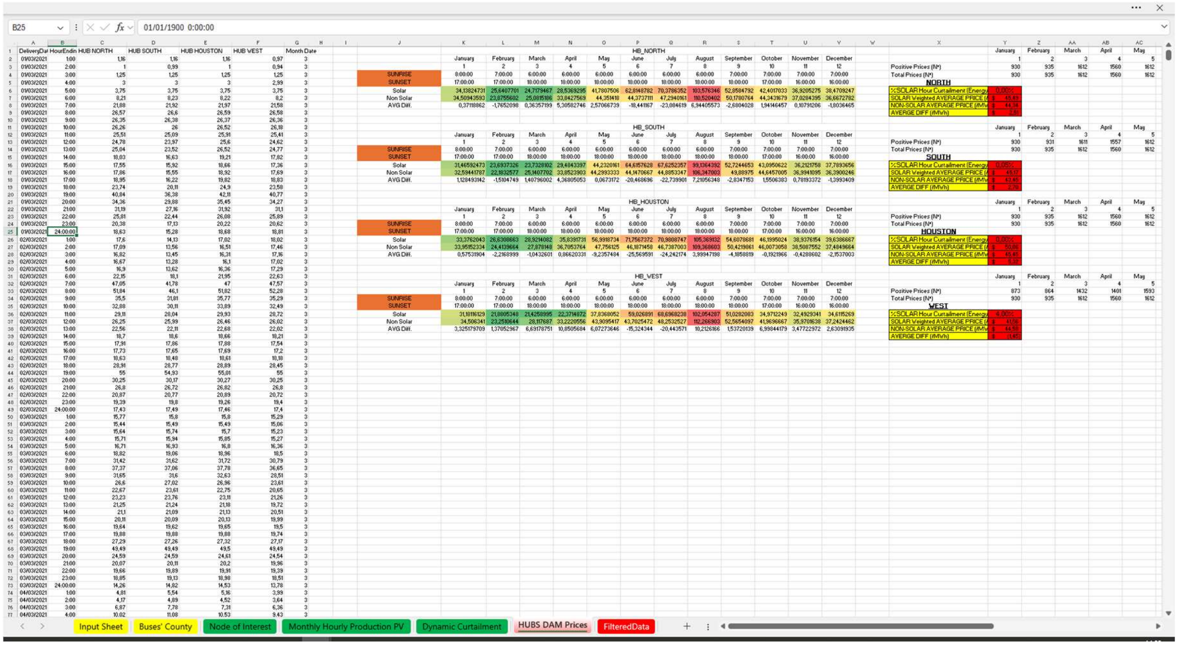


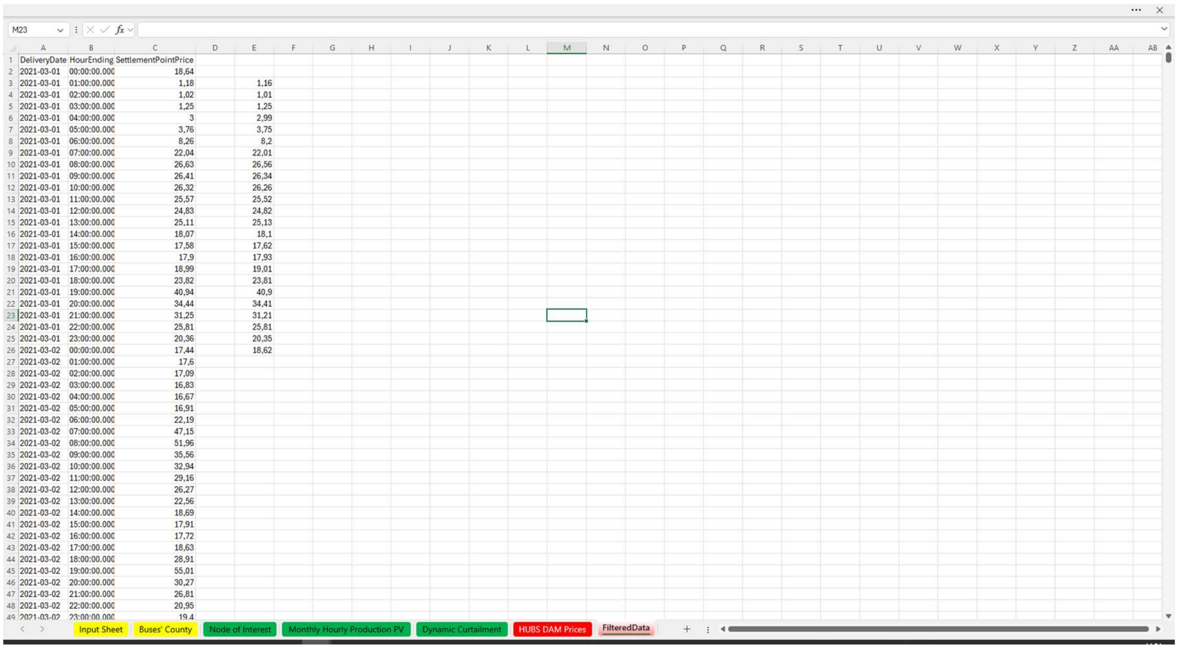

REFRESH DATA
Node of Analysis
HUB
CHOOSE HERE
NORTH
Input Sheet
Buses' County
Node of Interest
Monthly Hourly Production PV
Dynamic Curtailment
HUBS DAM Prices
FilteredData


Input Sheet
Buses' County
Node of Interest
Monthly Hourly Production PV
Dynamic Curtailment
HUBS DAM Prices
FilteredData


Input Sheet
Buses' County
Node of Interest
Monthly Hourly Production PV
Dynamic Curtailment
HUBS DAM Prices
FilteredData

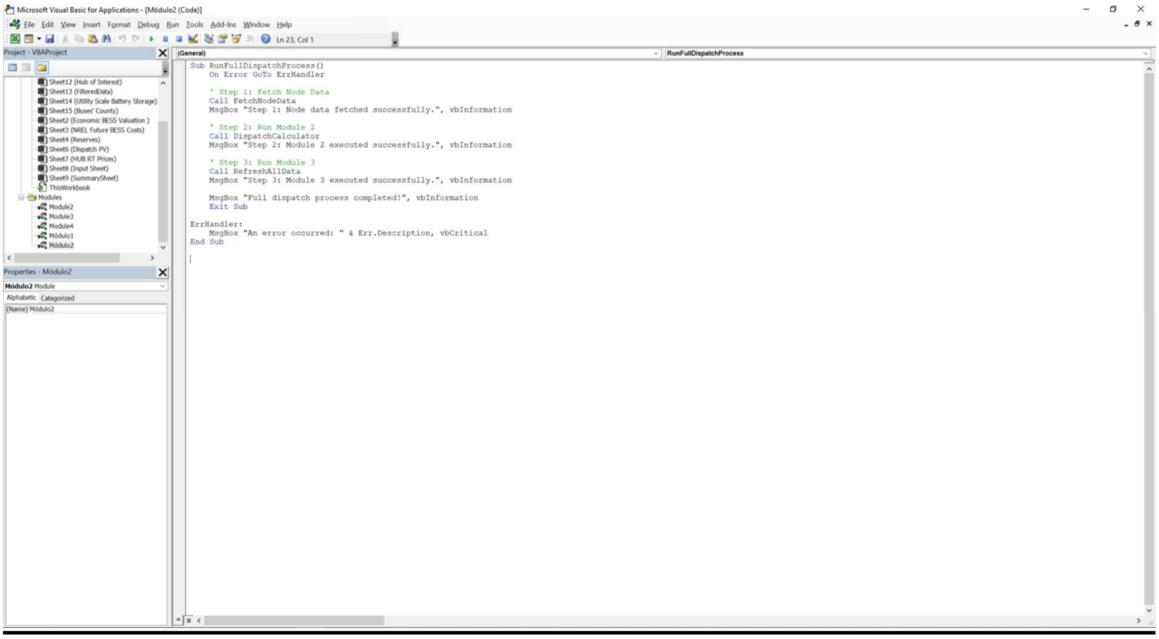

Curtailment Hours
NORMALIZED Production /100MW
Node of Interest
Monthly Hourly Production PV
Dynamic Curtailment
HUBS DAM Prices
FilteredData



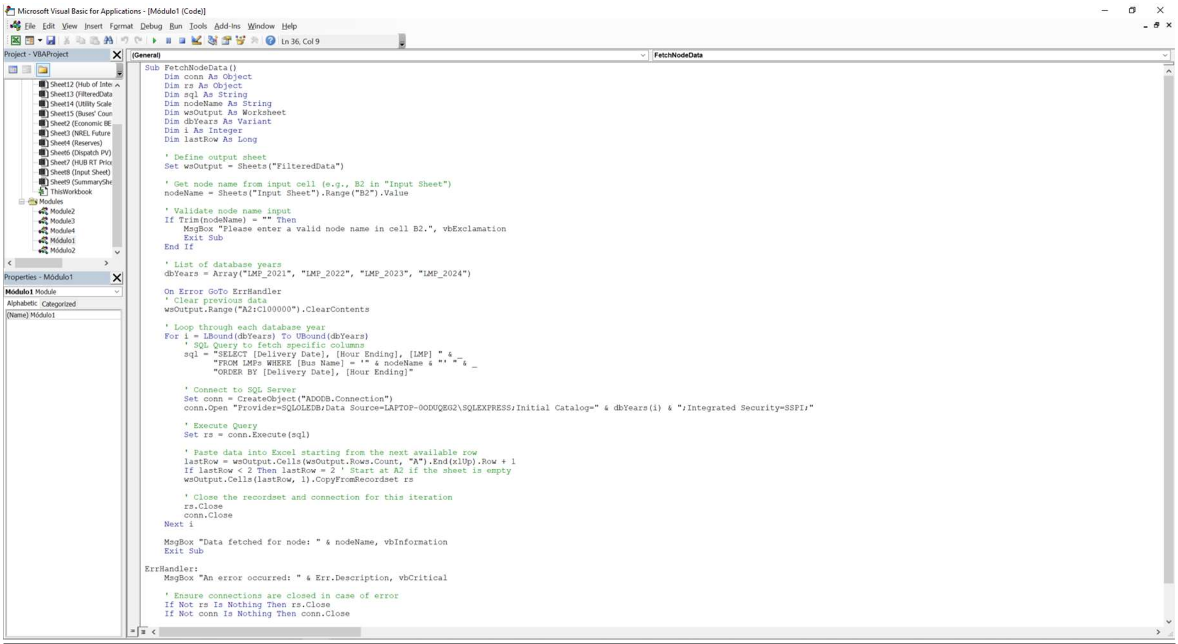


DeliveryDate	HourEnding	SettlementPointPrice		
2021-03-01	00:00:00.000	18,64		
2021-03-01	01:00:00.000	1,18		1,16
2021-03-01	02:00:00.000	1,02		1,01
2021-03-01	03:00:00.000	1,25		1,25
2021-03-01	04:00:00.000	3		2,99
2021-03-01	05:00:00.000	3,76		3,75
2021-03-01	06:00:00.000	8,26		8,2
2021-03-01	07:00:00.000	22,04		22,01
2021-03-01	08:00:00.000	26,63		26,56
2021-03-01	09:00:00.000	26,41		26,34
2021-03-01	10:00:00.000	26,32		26,26
2021-03-01	11:00:00.000	25,57		25,52
2021-03-01	12:00:00.000	24,83		24,82
2021-03-01	13:00:00.000	25,11		25,13
2021-03-01	14:00:00.000	18,07		18,1
2021-03-01	15:00:00.000	17,58		17,62
2021-03-01	16:00:00.000	17,9		17,93
2021-03-01	17:00:00.000	18,99		19,01
2021-03-01	18:00:00.000	23,82		23,81
2021-03-01	19:00:00.000	40,94		40,9
2021-03-01	20:00:00.000	34,44		34,41
2021-03-01	21:00:00.000	31,25		31,21
2021-03-01	22:00:00.000	25,81		25,81
2021-03-01	23:00:00.000	20,36		20,35
2021-03-02	00:00:00.000	17,44		18,62
2021-03-02	01:00:00.000	17,6		
2021-03-02	02:00:00.000	17,09		
2021-03-02	03:00:00.000	16,83		
2021-03-02	04:00:00.000	16,67		
2021-03-02	05:00:00.000	16,91		
2021-03-02	06:00:00.000	22,19		
2021-03-02	07:00:00.000	47,15		
2021-03-02	08:00:00.000	51,96		
2021-03-02	09:00:00.000	35,56		
2021-03-02	10:00:00.000	32,94		
2021-03-02	11:00:00.000	29,16		
2021-03-02	12:00:00.000	26,27		
2021-03-02	13:00:00.000	22,56		
2021-03-02	14:00:00.000	18,69		
2021-03-02	15:00:00.000	17,91		
2021-03-02	16:00:00.000	17,72		
2021-03-02	17:00:00.000	18,63		
2021-03-02	18:00:00.000	28,91		
2021-03-02	19:00:00.000	55,01		
2021-03-02	20:00:00.000	30,27		
2021-03-02	21:00:00.000	26,81		
2021-03-02	22:00:00.000	20,95		
2021-03-02	23:00:00.000	19,4		

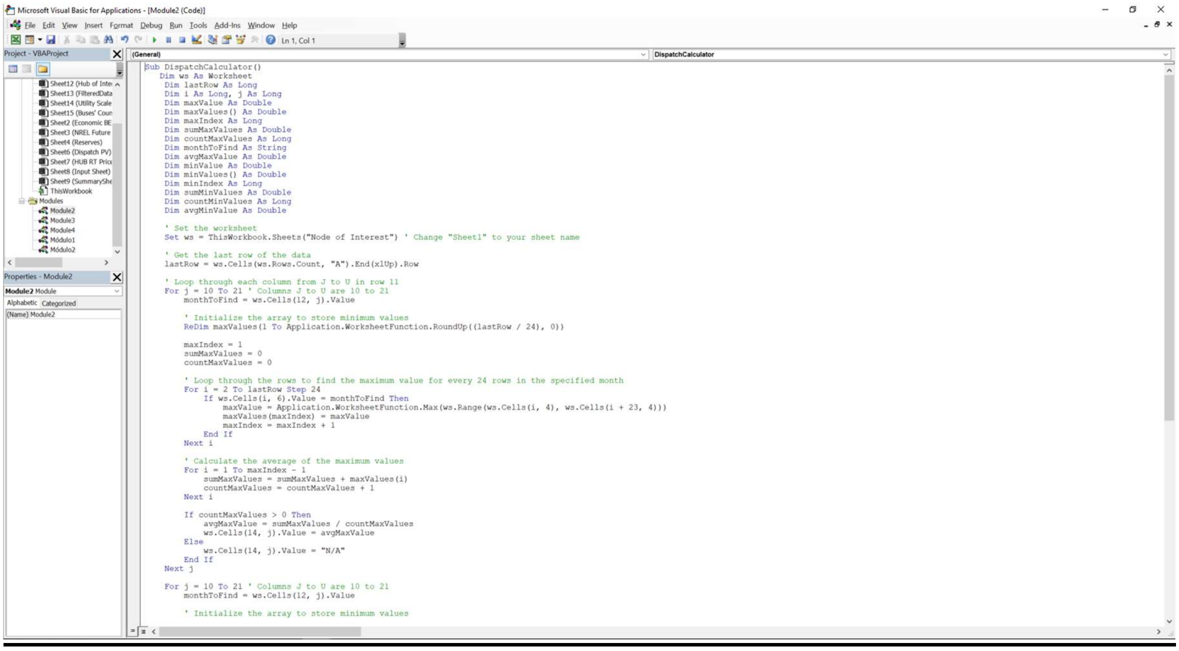
ANNEX IV. BATTERY VALUATION VBA CODE DISPATCH



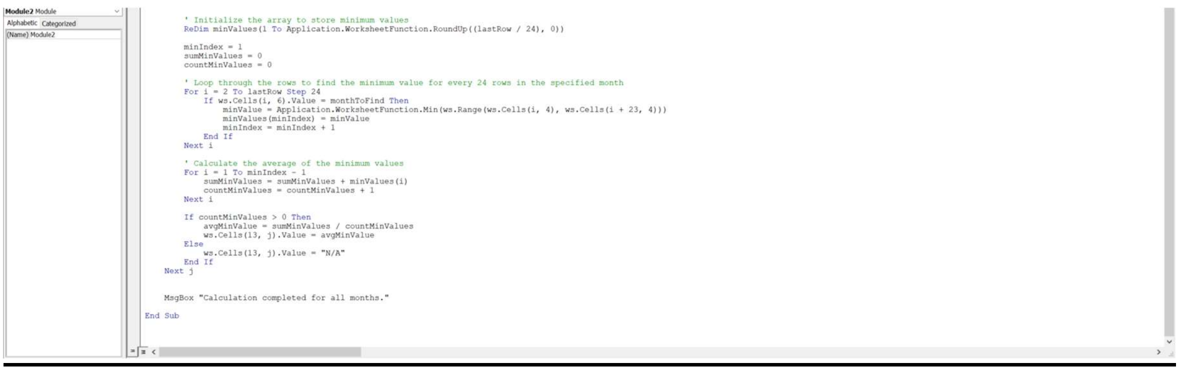
```vba
Sub RunFullDispatchProcess()
    On Error GoTo ErrHandler

    ' Step 1: Fetch Node Data
    Call FetchNodeData
    MsgBox "Step 1: Node data fetched successfully.", vbInformation

    ' Step 2: Run Module 2
    Call DispatchCalculator
    MsgBox "Step 2: Module 2 executed successfully.", vbInformation

    ' Step 3: Run Module 3
    Call RefreshAllData
    MsgBox "Step 3: Module 3 executed successfully.", vbInformation

    MsgBox "Full dispatch process completed!", vbInformation
    Exit Sub

ErrHandler:
    MsgBox "An error occurred: " & Err.Description, vbCritical
End Sub
```



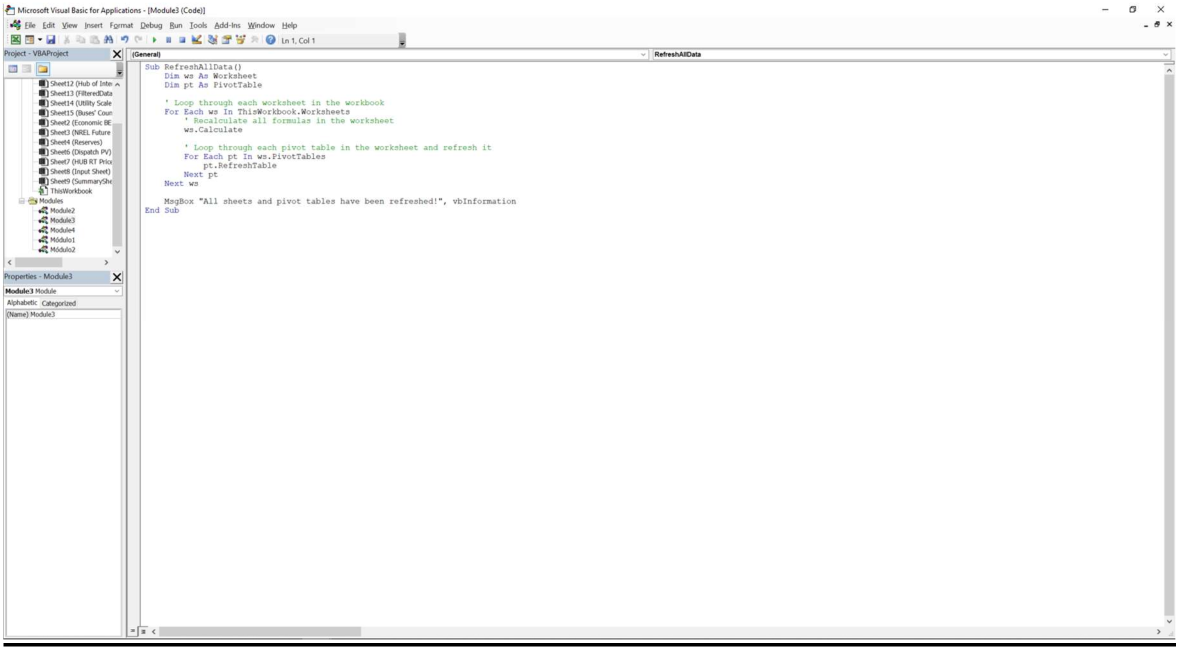
```vba
Sub FetchNodeData()
    Dim conn As Object
    Dim rs As Object
    Dim sql As String
    Dim nodeName As String
    Dim wsOutput As Worksheet
    Dim dbYears As Variant
    Dim i As Integer
    Dim lastRow As Long

    ' Define output sheet
    Set wsOutput = Sheets("FilteredData")

    ' Get node name from input cell (e.g., B2 in "Input Sheet")
    nodeName = Sheets("Input Sheet").Range("B2").Value

    ' Validate node name input
    If Trim(nodeName) = "" Then
        MsgBox "Please enter a valid node name in cell B2.", vbExclamation
        Exit Sub
    End If

    ' List of database years
    dbYears = Array("LMP_2021", "LMP_2022", "LMP_2023", "LMP_2024")

    On Error GoTo ErrHandler
    ' Clear previous data
    wsOutput.Range("A2:C100000").ClearContents

    ' Loop through each database year
    For i = LBound(dbYears) To UBound(dbYears)
        ' SQL Query to fetch specific columns
        sql = "SELECT [Delivery Date], [Hour Ending], [LMP] " & _
              "FROM LMPs WHERE [Bus Name] = '" & nodeName & "' " & _
              "ORDER BY [Delivery Date], [Hour Ending]"

        ' Connect to SQL Server
        Set conn = CreateObject("ADODB.Connection")
        conn.Open "Provider=SQLOLEDB;Data Source=LAPTOP-0ODUQEG2\SQLEXPRESS;Initial Catalog=" & dbYears(i) & ";Integrated Security=SSPI;"

        ' Execute Query
        Set rs = conn.Execute(sql)

        ' Paste data into Excel starting from the next available row
        lastRow = wsOutput.Cells(wsOutput.Rows.Count, "A").End(xlUp).Row + 1
        If lastRow < 2 Then lastRow = 2 ' Start at A2 if the sheet is empty
        wsOutput.Cells(lastRow, 1).CopyFromRecordset rs

        ' Close the recordset and connection for this iteration
        rs.Close
        conn.Close
    Next i

    MsgBox "Data fetched for node: " & nodeName, vbInformation
    Exit Sub

ErrHandler:
    MsgBox "An error occurred: " & Err.Description, vbCritical

    ' Ensure connections are closed in case of error
    If Not rs Is Nothing Then rs.Close
    If Not conn Is Nothing Then conn.Close
```



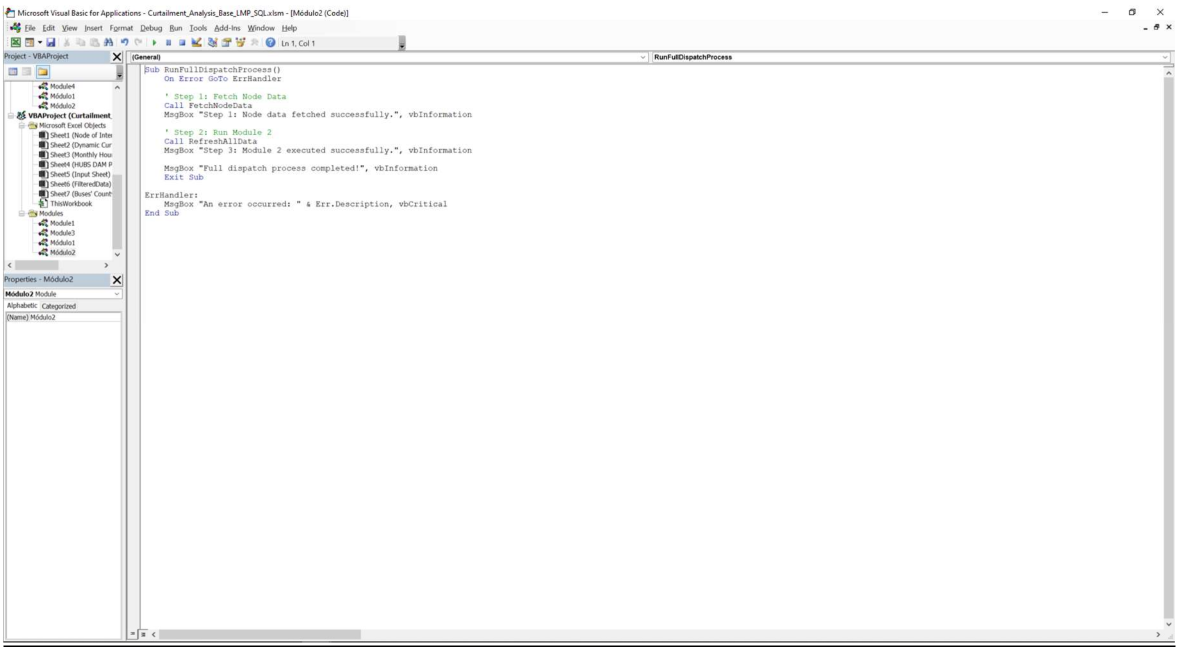
```
Sub DispatchCalculator()
    Dim ws As Worksheet
     Dim lastRow As Long
     Dim i As Long, j As Long
     Dim maxValue As Double
     Dim maxValues() As Double
     Dim maxIndex As Long
     Dim sumMaxValues As Double
     Dim countMaxValues As Long
     Dim monthToFind As String
     Dim avgMaxValue As Double
     Dim minValue As Double
     Dim minValues() As Double
     Dim minIndex As Long
     Dim sumMinValues As Double
     Dim countMinValues As Long
     Dim avgMinValue As Double

     ' Set the worksheet
     Set ws = ThisWorkbook.Sheets("Node of Interest") ' Change "Sheet1" to your sheet name

     ' 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 = 2 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
```

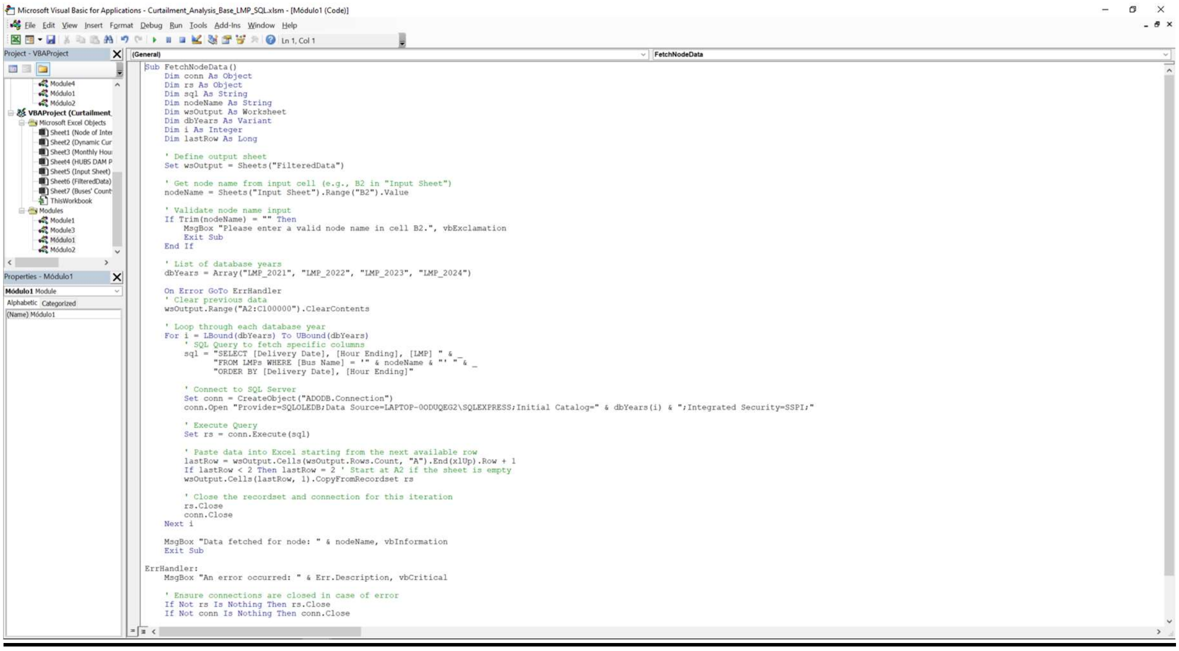


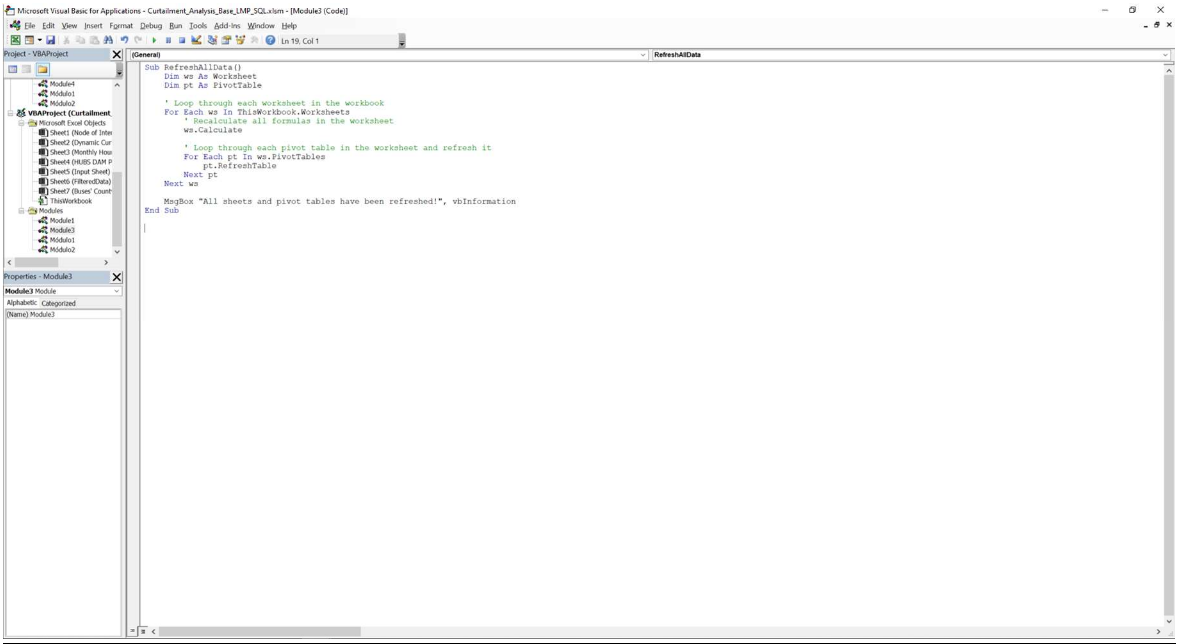
```
         ' Initialize the array to store minimum values
         ReDim minValues(1 To Application.WorksheetFunction.RoundUp((lastRow / 24), 0))

         minIndex = 1
         sumMinValues = 0
         countMinValues = 0

         ' Loop through the rows to find the minimum value for every 24 rows in the specified month
         For i = 2 To lastRow Step 24
             If ws.Cells(i, 6).Value = monthToFind Then
                 minValue = Application.WorksheetFunction.Min(ws.Range(ws.Cells(i, 4), ws.Cells(i + 23, 4)))
                 minValues(minIndex) = minValue
                 minIndex = minIndex + 1
             End If
         Next i

         ' Calculate the average of the minimum values
         For i = 1 To minIndex - 1
             sumMinValues = sumMinValues + minValues(i)
             countMinValues = countMinValues + 1
         Next i

         If countMinValues > 0 Then
             avgMinValue = sumMinValues / countMinValues
             ws.Cells(13, j).Value = avgMinValue
         Else
             ws.Cells(13, j).Value = "N/A"
         End If
     Next j


     MsgBox "Calculation completed for all months."

End Sub
```



ANNEX V. CURTAILMENT ANALYSIS VBA CODE DISPATCH




Microsoft Visual Basic for Applications - Curtailment_Analysis_Base_LMP_SQL.xlsm - [Módulo1 (Code)]
(General)
FetchNodeData
Sub FetchNodeData()
Dim conn As Object
Dim rs As Object
Dim sql As String
Dim nodeName As String
Dim wsOutput As Worksheet
Dim dbYears As Variant
Dim i As Integer
Dim lastRow As Long
' Define output sheet
Set wsOutput = Sheets("FilteredData")
' Get node name from input cell (e.g., B2 in "Input Sheet")
nodeName = Sheets("Input Sheet").Range("B2").Value
' Validate node name input
If Trim(nodeName) = "" Then
MsgBox "Please enter a valid node name in cell B2.", vbExclamation
Exit Sub
End If
' List of database years
dbYears = Array("LMP_2021", "LMP_2022", "LMP_2023", "LMP_2024")
On Error GoTo ErrHandler
' Clear previous data
wsOutput.Range("A2:C100000").ClearContents
' Loop through each database year
For i = LBound(dbYears) To UBound(dbYears)
' SQL Query to fetch specific columns
sql = "SELECT [Delivery Date], [Hour Ending], [LMP] " & _
"FROM LMPs WHERE [Bus Name] = '" & nodeName & "' " & _
"ORDER BY [Delivery Date], [Hour Ending]"
' Connect to SQL Server
Set conn = CreateObject("ADODB.Connection")
conn.Open "Provider=SQLOLEDB;Data Source=LAPTOP-0ODUQEG2\SQLEXPRESS;Initial Catalog=" & dbYears(i) & ";Integrated Security=SSPI;"
' Execute Query
Set rs = conn.Execute(sql)
' Paste data into Excel starting from the next available row
lastRow = wsOutput.Cells(wsOutput.Rows.Count, "A").End(xlUp).Row + 1
If lastRow < 2 Then lastRow = 2 ' Start at A2 if the sheet is empty
wsOutput.Cells(lastRow, 1).CopyFromRecordset rs
' Close the recordset and connection for this iteration
rs.Close
conn.Close
Next i
MsgBox "Data fetched for node: " & nodeName, vbInformation
Exit Sub
ErrHandler:
MsgBox "An error occurred: " & Err.Description, vbCritical
' Ensure connections are closed in case of error
If Not rs Is Nothing Then rs.Close
If Not conn Is Nothing Then conn.Close


Microsoft Visual Basic for Applications - Curtailment_Analysis_Base_LMP_SQL.xlsm - [Module3 (Code)]
(General)
RefreshAllData
Sub RefreshAllData()
Dim ws As Worksheet
Dim pt As PivotTable
' Loop through each worksheet in the workbook
For Each ws In ThisWorkbook.Worksheets
' Recalculate all formulas in the worksheet
ws.Calculate
' Loop through each pivot table in the worksheet and refresh it
For Each pt In ws.PivotTables
pt.RefreshTable
Next pt
Next ws
MsgBox "All sheets and pivot tables have been refreshed!", vbInformation
End Sub

ANNEX VI. BATTERY VALUATION PYTHON CODE DISPATCH

```
import os
import pandas as pd
from openpyxl import load_workbook
import win32com.client

# Define the directory containing the CSV files
directory = r'C:\Users\isang\Desktop\SOLEA POWER CORP\LMPs_March2021_now'

# Define the path to the Excel file containing the name to filter by
input_excel_path = r'C:\Users\isang\Desktop\SOLEA POWER CORP\2HR_BatteryValuation_LMP.xlsm'

# Check if the input Excel file exists
if not os.path.exists(input_excel_path):
    raise FileNotFoundError(f"The file {input_excel_path} does not exist.")

# Read the node name from the Excel sheet
try:
    input_df = pd.read_excel(input_excel_path, sheet_name='Input Sheet', engine='openpyxl')  # Adjust the sheet name as necessary
    name_to_filter = input_df.iloc[0, 1]  # Assuming the name is in cell B2
except Exception as e:
    raise Exception(f"An error occurred while reading the Excel file: {e}")

# Initialize an empty DataFrame to hold the merged data
merged_df = pd.DataFrame()

# Loop through all files in the directory
for filename in os.listdir(directory):
    if filename.endswith(".csv"):
        # Construct the full file path
        file_path = os.path.join(directory, filename)

        # Read the CSV file into a DataFrame
        try:
            df = pd.read_csv(file_path)
        except Exception as e:
            print(f"Error reading {file_path}: {e}")
            continue

        # Filter rows where the third column matches the specified name
```

```
        filtered_df = df[df.iloc[:, 2] == name_to_filter]

        # Append the filtered rows to the merged DataFrame
        merged_df = pd.concat([merged_df, filtered_df], ignore_index=True)

# Create a temporary Excel file with the filtered data
temp_excel_path = r'C:\Users\isang\Desktop\SOLEA POWER
CORP\temp_filtered_data.xlsx'
merged_df.to_excel(temp_excel_path, index=False, sheet_name='FilteredData')

# 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}")

    # Run the macros in the new workbook
    xl = win32com.client.Dispatch("Excel.Application")
    xl.Visible = False
    wb = xl.Workbooks.Open(Filename=new_excel_path, ReadOnly=False)

    # Run the specified macros
    xl.Application.Run(f'{wb.Name}!DispatchCalculator')
    xl.Application.Run(f'{wb.Name}!RefreshAllData')

    # Save the workbook after running the macros
    wb.Save()
    wb.Close(SaveChanges=True)

        print(f"Macros DispatchCalculator, RefreshAllData, and
DispatchCalculatorHub have been executed and the workbook has been saved.")
except Exception as e:
    raise Exception(f"An error occurred while writing to the Excel file or
running macros: {e}")
finally:
    # Ensure the Excel application is properly closed and quit
    if 'xl' in locals():
        xl.Quit()

    # Delete the temporary file
    try:
        if os.path.exists(temp_excel_path):
            os.remove(temp_excel_path)
            print(f"Temporary file {temp_excel_path} has been deleted.")
    except Exception as e:
        print(f"An error occurred while deleting the temporary file: {e}")
```

ANNEX VII. CURTAILMENT ANALYSIS PYTHON CODE DISPATCH

```
import os
import pandas as pd
from openpyxl import load_workbook
import win32com.client

# Define the directory containing the CSV files
directory = r'C:\Users\isang\Desktop\SOLEA POWER CORP\LMPs_March2021_now'

# Define the path to the Excel file containing the name to filter by
input_excel_path = r'C:\Users\isang\Desktop\SOLEA POWER CORP\Curtailment Analysis Base LMP.xlsm'

# Check if the input Excel file exists
if not os.path.exists(input_excel_path):
    raise FileNotFoundError(f"The file {input_excel_path} does not exist.")

# Read the node name from the Excel sheet
try:
    input_df = pd.read_excel(input_excel_path, sheet_name='Input Sheet', engine='openpyxl')  # Adjust the sheet name as necessary
    name_to_filter = input_df.iloc[0, 1]  # Assuming the name is in cell B2
except Exception as e:
    raise Exception(f"An error occurred while reading the Excel file: {e}")

# Initialize an empty DataFrame to hold the merged data
merged_df = pd.DataFrame()

# Loop through all files in the directory
for filename in os.listdir(directory):
    if filename.endswith(".csv"):
        # Construct the full file path
        file_path = os.path.join(directory, filename)

        # Read the CSV file into a DataFrame
        try:
            df = pd.read_csv(file_path)
        except Exception as e:
            print(f"Error reading {file_path}: {e}")
            continue

        # Filter rows where the third column matches the specified name
```

```
        filtered_df = df[df.iloc[:, 2] == name_to_filter]

        # Append the filtered rows to the merged DataFrame
        merged_df = pd.concat([merged_df, filtered_df], ignore_index=True)

# Create a temporary Excel file with the filtered data
temp_excel_path = r'C:\Users\isang\Desktop\SOLEA POWER
CORP\temp_filtered_data.xlsx'
merged_df.to_excel(temp_excel_path, index=False, sheet_name='FilteredData')

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

    # Copy data from "Input Sheet" to "SummarySheet"
    input_sheet = book['Input Sheet']
    summary_sheet = book['Node of Interest']
    summary_sheet['C3'] = input_sheet['B2'].value
    summary_sheet['I17'] = 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}Curtail.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}")

    # Run the macros in the new workbook
    xl = win32com.client.Dispatch("Excel.Application")
    xl.Visible = False
    wb = xl.Workbooks.Open(Filename=new_excel_path, ReadOnly=False)

    # Run the specified macros
    xl.Application.Run(f'{wb.Name}!RefreshAllData')

    # Save the workbook after running the macros
    wb.Save()
    wb.Close(SaveChanges=True)

    print(f"Macros RefreshAllData have been executed and the workbook has
been saved.")
except Exception as e:
    raise Exception(f"An error occurred while writing to the Excel file or
running macros: {e}")
finally:
    # Ensure the Excel application is properly closed and quit
    if 'xl' in locals():
        xl.Quit()

    # Delete the temporary file
    try:
        if os.path.exists(temp_excel_path):
            os.remove(temp_excel_path)
            print(f"Temporary file {temp_excel_path} has been deleted.")
    except Exception as e:
        print(f"An error occurred while deleting the temporary file: {e}")
```