Battery Energy Storage Analysis

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The Data at a Glance:

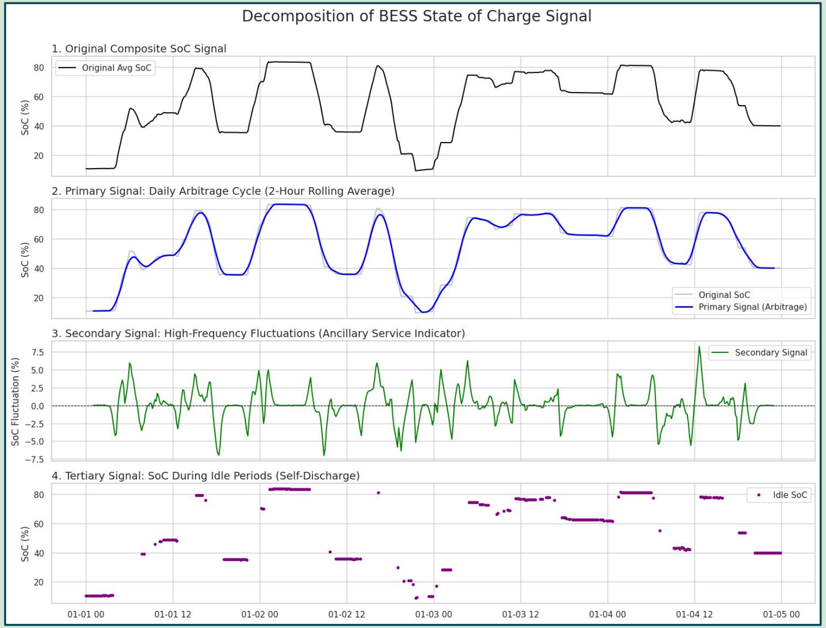
Day	Clock Time	BESS SoC 1	BESS SoC 2	Max Power Export [MW]	Max Power Import [MW]	Max Temp (degrees C)	Min Temp (degrees C)	Power [MW]
1	0:00:00	9.50%	11.60%	60.53	90.53	49.3	9.1	-0.3
1	0:10:00	9.50%	11.70%	53.16	89.47	49.6	9.1	-0.71
1	0:20:00	9.40%	11.60%	64.74	89.47	49.2	9.1	2.85
1	0:30:00	9.40%	11.50%	42.89	89.47	49.1	9.0	-0.92
1	0:40:00	9.40%	11.60%	42.79	89.47	49.0	9.0	-0.87
1	0:50:00	9.40%	11.60%	42.68	89.47	48.9	9.0	-0.87

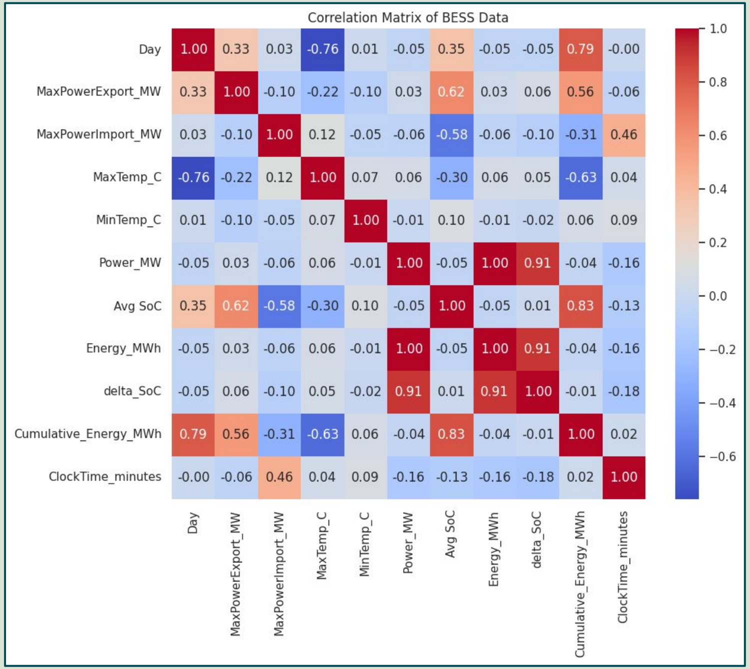
Scope: 4 days of continuous BESS operations

Granularity: High-frequency data captured every 10 minutes.

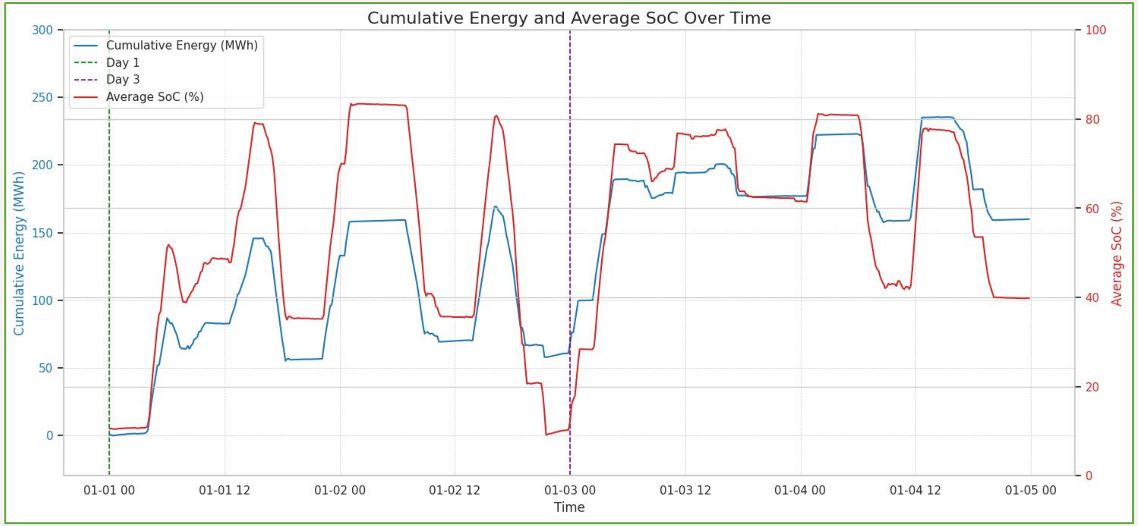
Content: Includes state of charge(SoC), operational power, hardware constraints, and thermal health data.

The Data at a Glance: EDA





The Data at a Glance: Energy In, Energy Out



What We See:

The BESS performed multiple charge/discharge cycles, closely following a daily pattern.

- Charging (SoC increases): Cumulative Energy goes up.
- Discharging (SoC decreases): Cumulative Energy goes down.

Key Observation:

But notice that for a given time period (eg: Day 1 to Day 3) , when the SoC goes from 10% -> 80% -> 10%, the cumulative energy in the same time period doesn't return to zero.

This gap represents energy loss while charging/discharging.

Key Finding #1: Cycles

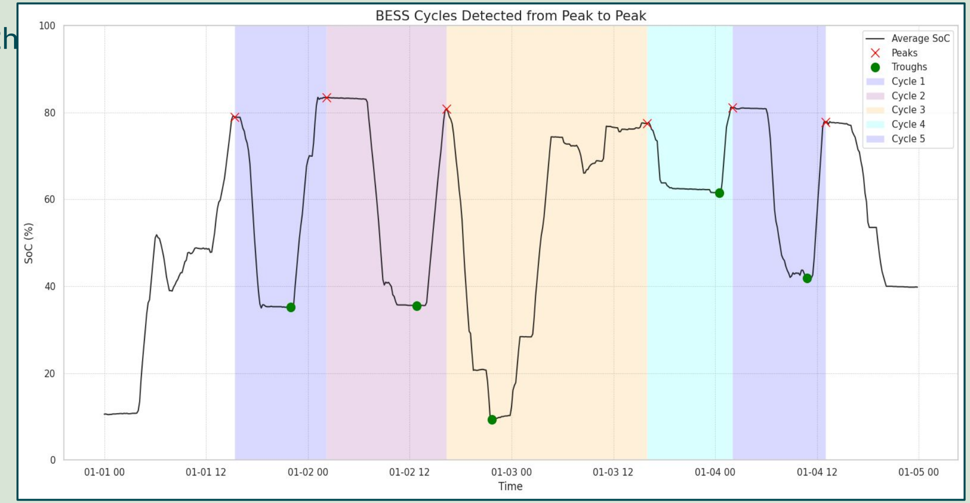
Cycle Timing & Strategy of BESS:

Evening Peak Discharge (Cycles 1, 3, 4):

- Starts between 15:20–16:20, aligning with peak demand and prices.
- Cycle 3 spans nearly 24 hours: slow 18.5h charge, fast 5.2h discharge.

Early Morning Charging (Cycles 2, 5):

- Starts around 02:00 when grid demand/prices are lowest.
- Rapid charge phases (e.g.3.3h for Cycle 2) prepare for daytime discharge.



Round-Trip Efficiency (RTE):

- Cycles 1, 2, 5: Good Normalized RTE (79–95%).
- Cycles 3, 4: Low RTE (~67%)
- Total: (~76%)

The Business Impact:
RTE of 67% means we lose a third of the money we spend on charging.

Likely Cause: Long duration cycles amplify fixed losses (cooling, idle drain, etc.).

Key Finding #2: Metrics

Total Energy Capacity:

211 MWh

Rated Power Capacity:

100 MW

Maximum Observed Power:

60-65 MW

Round-Trip Efficiency (RTE):

79%

Max Ramp Rate:

6.4 MW/min

Thermal Gradient:

~40 C

Storage Duration:

2.1 hrs

Model #1: SoC Constraints

Isotonic Regression Model for Power Limits

- ➢ Models ‘Max Import/Export Power’ as a function of ‘SoC’
- ➢ Captures real-world tapering behavior effectively

Discharge (Export) Behavior:

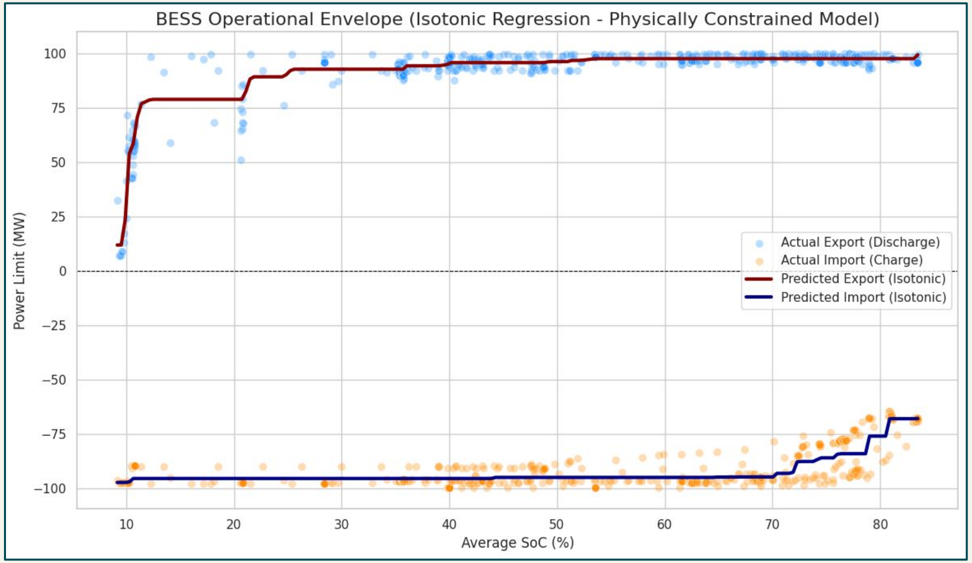
- Full Power Zone: 25%–85% SoC → up to 100 MW
- Low SoC Derating: Below 25% → export power gradually reduced to protect battery

Charge (Import) Behavior:

- Full Power Zone: 10%–70% SoC → up to 100 MW
- High SoC Derating: Above 70% → import power reduced to prevent overcharging

Key Takeaway:

- ➢ SoC is the dominant constraint on BESS operation
- ➢ Optimization strategies must consider SoC tapering near limits for safety and performance

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--- Isotonic Regression Model Performance ---

Export Power Model
Mean Squared Error (MSE): 14.42
R-squared (R2): 0.93

Import Power Model
Mean Squared Error (MSE): 22.56
R-squared (R2): 0.78
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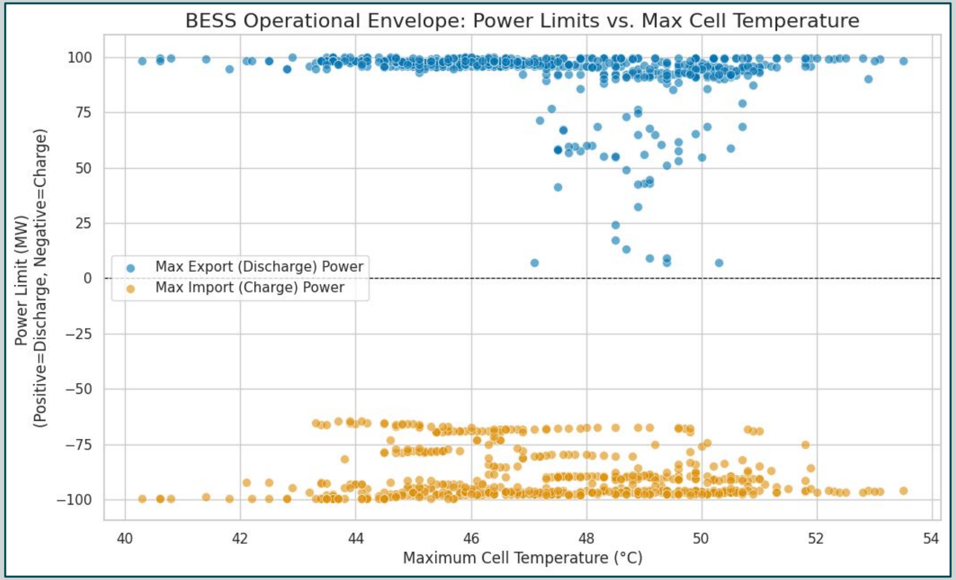
Model #2: Thermal Constraints

Good News: The BESS consistently delivers full charge/discharge power (~100 MW) across the entire observed temperature range (40°C to 53°C).

The dips in power are caused by the SoC limits, **not by heat**.



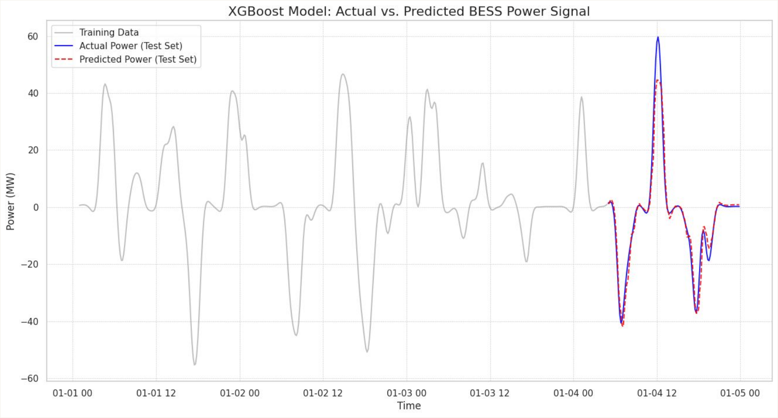
Model #3: Predicting Power Levels in Future

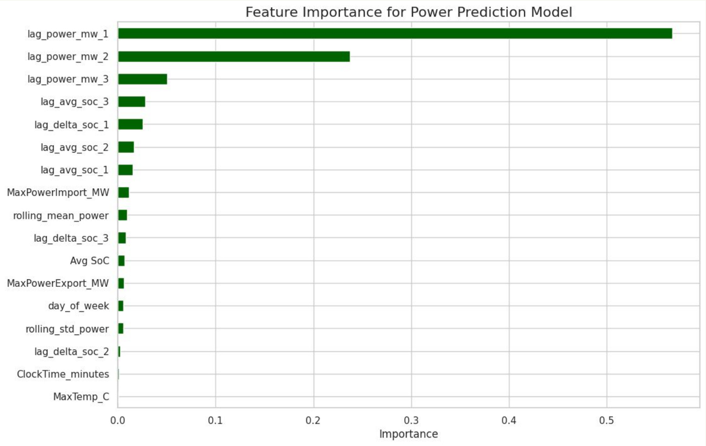
It is possible to accurately forecast the BESS's Power Level.

An **XGBoost** model was used to predict the core power dispatch signal (lowpass signal).

Result: The model achieved an R^2 of 0.95 and MSE = 2.57 on unseen data, showing high test accuracy.

Key Drivers: The most important factors are recent changes in power, and the recent past avg SoC.





Optimizer Model

I built an optimization model using cvxpy that uses all the previous constraints and BESS specs:

Capacity, Max Power, Efficiency, Ramp Rate
SoC-dependent power limits (the "tapering" curves), etc.

The Goal: Maximize profit using our current BESS against a simulated 24-hour price signal.

The Result:

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Solver Status: optimal
Total Revenue from Discharging: $58,455.30
Total Cost of Charging:         $40,180.65
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Optimized Net Profit:           $18,274.65
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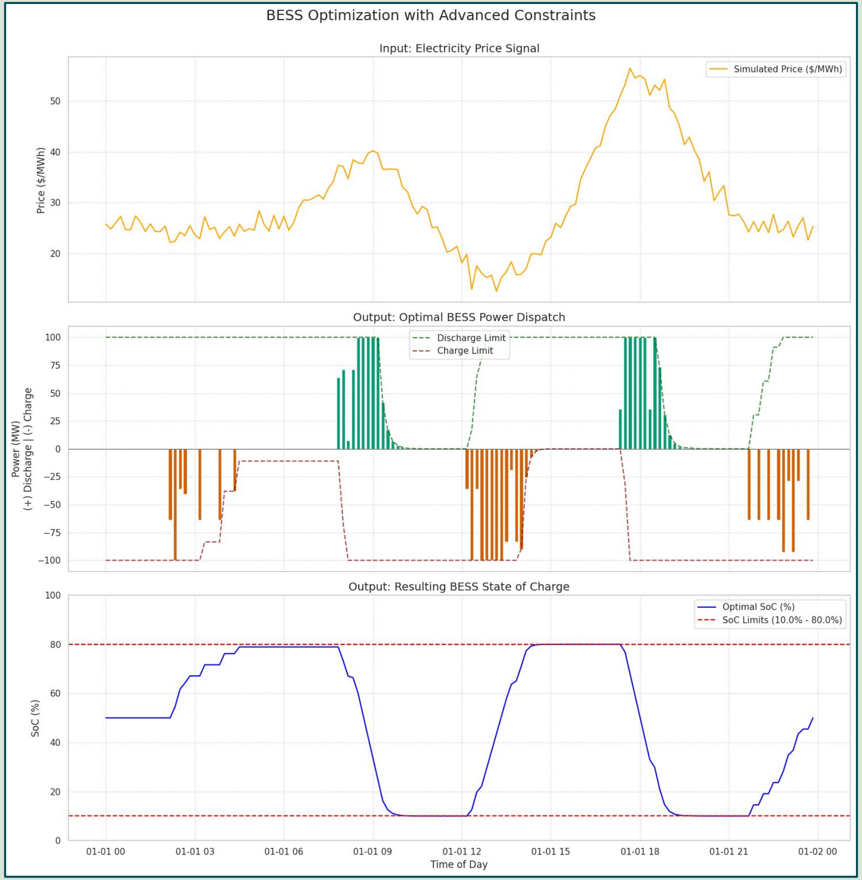

Next Steps

Dynamic Battery Model Data: Obtain Manufacturer data on how battery degradation and efficiency change with temperature, and state of charge.

Price Forecast Uncertainty Modeling: Firstly, real price data would help a lot. And instead of one perfect forecast, I'd want data to model a range of likely price scenarios to create a more robust, risk-aware strategy.

Real-World Operating Conditions: Data on local grid constraints and ambient temperature, sunlight, which directly impact the battery's performance and health.

Simulate Perfectly: I would try building high precision model to accurately simulate battery physics, aging, and thermal behavior, instead of the linear approximations I am using now.