Predicting Battery Energy Storage System (BESS) Degradation to Inform Pricing and Decision Making

BUSINESS PROBLEM

NextEra Energy Resources operates a rapidly expanding portfolio of Battery Energy Storage Systems (BESS) under long-term contracts (up to 20 years), yet most assets have only 2–3 years of operating history. Existing degradation models rely on lab-based cell testing and fail to reflect real-world system behavior. This creates uncertainty in ESA pricing, supplier warranty negotiations, and augmentation planning. With augmentation projects costing $3M–$20M and portfolio needs exceeding 1,600 MWh by 2033, the lack of operationally grounded forecasts limits optimization of multi-million-dollar decisions.

DATA SOURCES

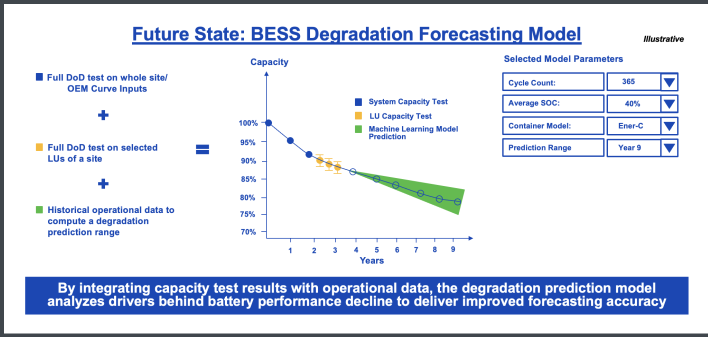
The project leverages three primary data streams: (1) BMS operational data covering cycle count, state of charge (SOC), depth of discharge (DoD), and ancillary dispatch signals from 16 CAISO liquid-cooled BESS sites; (2) site-level full depth-of-discharge capacity test results; and (3) line-up (LU) level capacity test data, automatically detected through a custom algorithm.

DATA TYPES AND FORMAT

Boolean, Categorical (nominal), Count (integer), Numeric, Time series (Dynamic)

APPROACH

To address gaps in BESS degradation forecasting, we develop a machine learning pipeline integrating operational telemetry with capacity test data. Features capture cycle count, SOC, depth of discharge, and dispatch use case. Correlation analysis validates feature relevance, showing strong negative relationships between capacity and both cumulative cycles and asset age. We evaluate regression and gradient boosting models to produce site-specific degradation curves with 90% confidence intervals, enabling scalable, on-demand forecasting across the portfolio.



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IMPACT

This project delivers a scalable, data-driven framework for BESS degradation forecasting that improves operational data increases, enhancing decision-making across the asset lifecycle. Engineers can quantify site-specific behavior – including dispatch mix, SOC distributions, and depth-of-discharge – and translate these into forward-looking degradation curves with confidence intervals.

Initial models show cycle count and days since commissioning explain over 60% of capacity variance (R^2 » 0.60), with accuracy improving as additional features are incorporated. The pipeline – validated across representative utility-scale sites – is designed for replication across the broader CAISO liquid cooled fleet.

Operationally, the framework reduces analysis time by ~50–70% and enables faster augmentation planning. Financially, improved forecasts can shift augmentation timing, driving ~5–10% cost optimization on $3M–$20M projects. Overall, it strengthens ESA pricing, warranty negotiations, and lifecycle value capture across a rapidly growing portfolio.

DRIVERS	Limited real-world degradation data for utility-scale BESS created uncertainty in ESA pricing, warranty negotiations, and augmentation planning. Lab-based models did not reflect operational behavior, exposing multi-million-dollar decisions to forecasting risk as the portfolio rapidly scales.
BARRIERS	Inconsistent telemetry tags and data availability across sites, limited historical depth (2–3 years), irregular capacity testing intervals, and noise in LU-level data. Integrating BMS, revenue meter, and test datasets required alignment and cleaning to ensure reliability for modeling.
ENABLERS	Access to multi-site operational data, standardized capacity testing protocols, and collaboration with engineering and analytics teams. Existing data infrastructure (BMS, revenue meter) and domain expertise enabled feature engineering and validation of degradation drivers.
ACTIONS	Integrated telemetry and capacity test data into a unified pipeline, engineered features capturing cycling, SOC, DoD, temperature, and dispatch regimes, and applied smoothing techniques to capacity curves. Developed and tested regression and ML models, validated feature relationships, and built a scalable framework for site-level forecasting with confidence intervals.
INNOVATION	Combines real-world operational telemetry with capacity test data to model degradation at system and lineup levels, rather than relying on lab-based assumptions. Introduces scalable feature engineering tied to dispatch behavior and applies monotonic smoothing to ensure physically consistent degradation trends across sites.
IMPROVEMENT	Improves visibility into site-specific degradation drivers and reduces reliance on conservative, lab-based assumptions. Enables more consistent and defensible decision-making for augmentation timing, ESA pricing, and warranty negotiations. Streamlines analysis workflows, accelerates insight generation, and enhances confidence in lifecycle planning across a growing portfolio.
BEST PRACTICES	Prioritize data quality and alignment over model complexity. Ensure consistent capacity testing cadence. Use physically grounded constraints (e.g., monotonic degradation). Focus on interpretable features tied to operations for stakeholder trust and decision usability.
OTHER APPLICATIONS	Applicable to other energy storage portfolios, EV fleet battery health monitoring, and renewable asset performance forecasting. Framework can extend to different chemistries, markets, and operational strategies where degradation impacts lifecycle economics.