Engineering | Energy | Predictive forecasting | Reinforcement learning

Predictive Model for Battery State of Health

BUSINESS PROBLEM

The main problem the business is trying to solve is the accurate estimation of the State of Health (SoH) of battery sites to inform and optimize their augmentation strategy. This is crucial for preventing both over- and under-augmentation of batteries, which can lead to unnecessary costs or insufficient capacity to meet contractual terms. With an accurate real-time SoH estimation, the business can plan timely augmentation and maintenance, minimize costs related to on-site capacity tests and associated downtime, and reduce expenses from suboptimal augmentation, ensuring efficient resource allocation and cost-effective operations.

DATA SOURCES

The data came from NextEra's central server, sourced from Battery Management Systems and on-site sensors. Additional business inputs for the case study came from the Business Management team and the Power Generation Division.

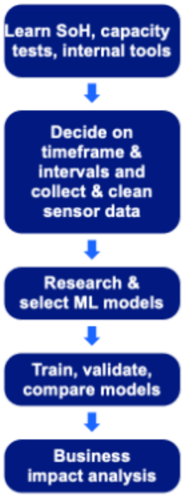
Data Types and Format

The data was time series format for current, voltage, temperature, State of Charge (SoC), and State of Health (SoH) from multiple battery sites.

Author: Catalina Garza Lozano

APPROACH

I utilized four models: a Kalman Filter, Long Short-Term Memory Recurrent Neural Network (RNN), Multitask RNN and Delayed Reinforcement Learning to predict the State of Health of battery sites using operational data such as current, voltage, temperature, and State of Charge. To evaluate the accuracy of these models, I validated predictions using internal capacity tests.



IMPACT

By providing accurate, real-time SoH assessments of utility-scale battery systems, the model enables more precise planning for augmentation, reducing both over- and under-augmentation. This leads to substantial capital expenditure savings by delaying augmentation until necessary and taking advantage of falling battery prices. It also minimizes operational inefficiencies and helps avoid penalties tied to underperformance in Power Purchase Agreements. The Delayed Reinforcement Learning model, in particular, achieved a 1.6-month prediction error—far outperforming the current Battery Management System (BMS), which had a 58-month error. Applied at scale, this level of accuracy could generate NPV savings in the millions across the fleet. Ultimately, the model supports smarter asset management, greater financial efficiency, and stronger compliance with contractual obligations, positioning NextEra to better manage the evolving demands of energy storage.

DRIVERS	The rapid growth of utility-scale energy storage, falling battery costs, and the performance obligations in long-term PPAs created a need for better battery health forecasting. The industry is facing challenges in planning augmentations efficiently due to limited SoH visibility, risking unnecessary costs or compliance issues. This gap catalyzed the development of a predictive SoH model to enable smarter, data-driven decision-making.
BARRIERS	Barriers included varying data quality across sites, limited capacity test data availability for some locations, and inconsistent data formats that required preprocessing. Additionally, training and tuning machine learning models demanded significant computational power, which limited the ability to rapidly test and iterate on different model architectures and hyperparameters.
ENABLERS	The company's scale and access to extensive data and resources enabled the project, along with a strong culture of collaboration. My team sat between engineering and supply chain, giving it broad visibility. Many team members had both consulting and engineering backgrounds, which helped bridge technical and business perspectives effectively throughout the project.
ACTIONS	To implement the solution, I learned how capacity tests work and how SoH is measured through them. I reviewed past approaches within the company to understand what had or hadn't worked. I researched SoH models in the literature and explored various machine learning algorithms, studying their implementation and identifying the best ways to run them efficiently in our context.
INNOVATION	The solution's innovation lies in applying machine learning to predict battery SoH using the daily operational data from the sites. The Delayed Reinforcement Learning model yielded interesting results and shows strong potential to be further developed for SoH prediction.
IMPROVEMENT	The final improvement was a significant increase in the accuracy of State of Health predictions. The best-performing model reduced prediction error from 58 months (using BMS data) to just 1.6 months. While there is still more work to be done, this improvement enables better augmentation planning, reduces unnecessary costs, and helps ensure compliance with long-term performance obligations.
BEST PRACTICES	To replicate this solution, start by understanding how SoH is measured and ensure access to clean, consistent time series data. Review prior internal attempts and relevant literature to build on existing knowledge. Test model types on a small scale, validate against real capacity test results, and balance computational complexity with practical usage. Collaboration across technical and business teams is key to delivering actionable outcomes.
OTHER APPLICATIONS	Beyond battery augmentation planning, this solution could be applied to warranty risk assessment, asset valuation, and predictive maintenance. It could also support portfolio-level planning, grid reliability analysis, and integration with energy trading strategies by providing more accurate, real-time insights into battery performance and degradation.