Maximizing Renewables and Energy Storage Profitability with AI-Based Optimization and Predictive Analytics

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Background

As portfolios of renewables and storage assets scale globally, asset owners, investors, managers, and traders across the globe are trying to achieve maximum financial returns for their portfolio. Maximizing returns requires:

Understanding how and why assets are performing today – and anticipating how they will perform in the future

Develop optimal short- and long-term plans for operating, maintaining, and bidding those assets into electricity markets

Implementing this for renewables and storage assets is more complex than doing so for other generation types because of the inherent complexity and quantity of data required to collect, analyze, and optimize:

Utility-scale solar assets produce 5x the data points than are produced by conventional generation assets, and storage assets may produce even 100x that amount1. SCADA alarms are typically so numerous and unprocessed, they are challenging to prioritize.

Bidding storage assets into electricity markets requires ingesting and analyzing more data than other asset types due to bidding across real-time and day ahead markets, across products, and are subject to warranty and operating constraints.

Objective

Artificial intelligence (AI) and machine learning (ML) can ingest, identify trends within, and learn to anticipate future outputs from large swaths of data that may be challenging for humans to handle. We seek to investigate how advanced digital solutions that leverage AI and ML can help renewable and storage asset owners, operators, and traders collect, analyze, and optimize the technical performance and financial returns of quickly scaling portfolios.

Methods

Financial impact can be measured through revenue uplift (additional revenue generated) or cost savings (avoided costs on operations, maintenance, and more). To quantify each of these metrics, we've run two analyses:

1.) Back-cast of AI-Based Storage Bidding Optimization: Year-long back-cast in the California ISO (CAISO) that simulates performance and market results from a manual trading method vs. an algorithmic trading solution that leverages AI-based price forecasting

2.) Historical Study of AI-Based Predictive Maintenance Alerts: Utilizing sample data from multiple real-world wind farms, we utilize a novel ML-based approach for early fault detection of wind turbine faults using alarms and warnings from the SCADA system.

Results

Revenue Uplift from AI-Powered Storage Bidding Optimization

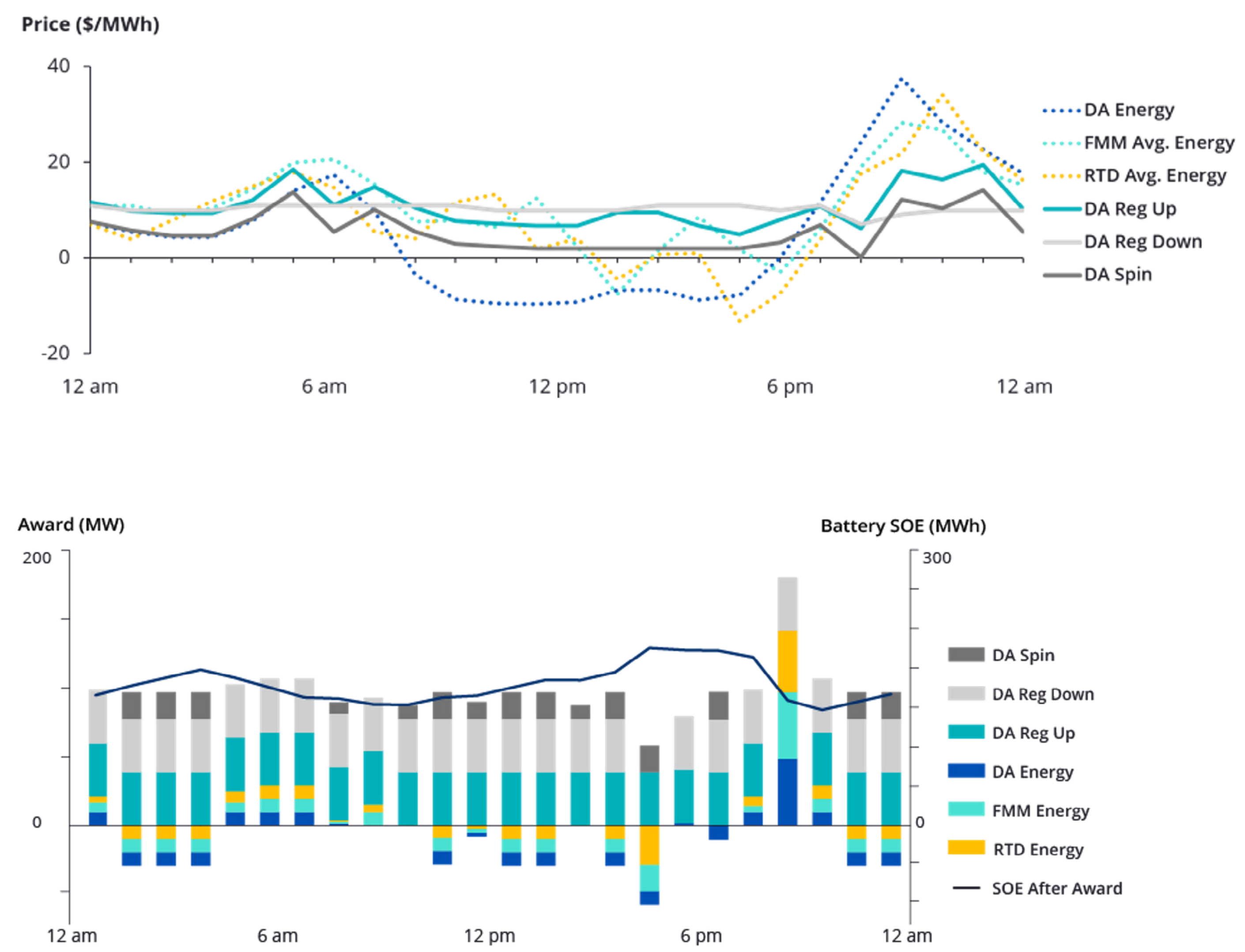

FIGURE 1: Example analysis performed with actual Day Ahead Market, Fifteen Minute Market, and Real Time Dispatch prices. Data covers pricing for May 28, 2019 at HAAS_7_B11 price node and NP-15 AS trading zone; 50MW/200MWh; 1 cycle / day limit; 93% charge efficiency and 95% discharge efficiency; regulation up & down cap of 50 MW.

In the revenue uplift analysis, both scenarios (algorithmic and manual bidding) simulate performance using specific asset characteristics (e.g., warranty constraints) and actual market price data. Fig. 1 shows how the battery is co-optimizing across market products while managing state of energy throughout the day with respect to market prices. Percent of Perfect (PoP) analysis compares revenue from algorithmic trading and maximum revenue that an asset could have attained if it had perfect knowledge of actual market prices (i.e., "perfect foresight"). PoP equals the Operational Foresight Scenario revenue as a percent of Perfect Foresight Scenario revenue. Fig. 2 compares the revenue from algorithmic and manual bidding and the PoP achieved by algorithmic trading.

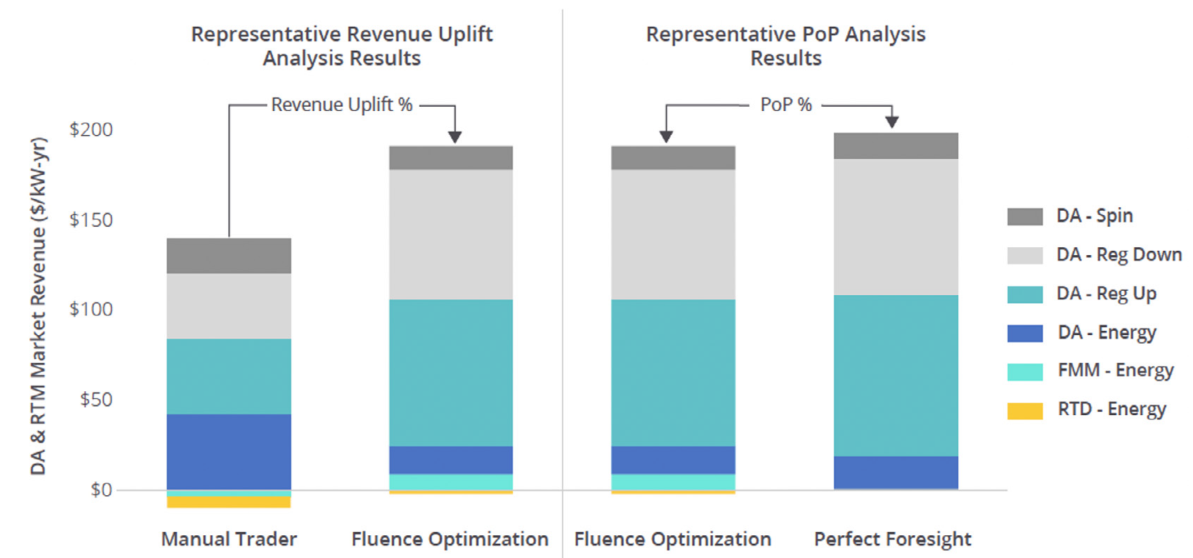

FIGURE 2: Example analysis performed with actual 2019 prices. Data includes prices at HAAS_7_B11 price node and NP-15 AS trading zone; 50MW/200MWh; 1 cycle / day limit; 93% charge efficiency and 95% discharge efficiency; regulation up & down cap of 50 MW

Cost Savings from AI-Based Preventative Maintenance Analytics for Renewables

Fault Event		
High Gearbox temperature		
Alarm	**Description**	
1	Alarm that stopped the turbine	
2	Alarm related to the oil pump (thermoerror)	
Feature	**from Alarm**	**Description**
A	1	Cumulated duration
B	2	No. of occurrences
C	1	No. of consecutive occurrences
D	1	Median Inter-Arrival Time
E	2	Max duration

TABLE 1: Example of fault, main alarms, and extracted features from the alarms.

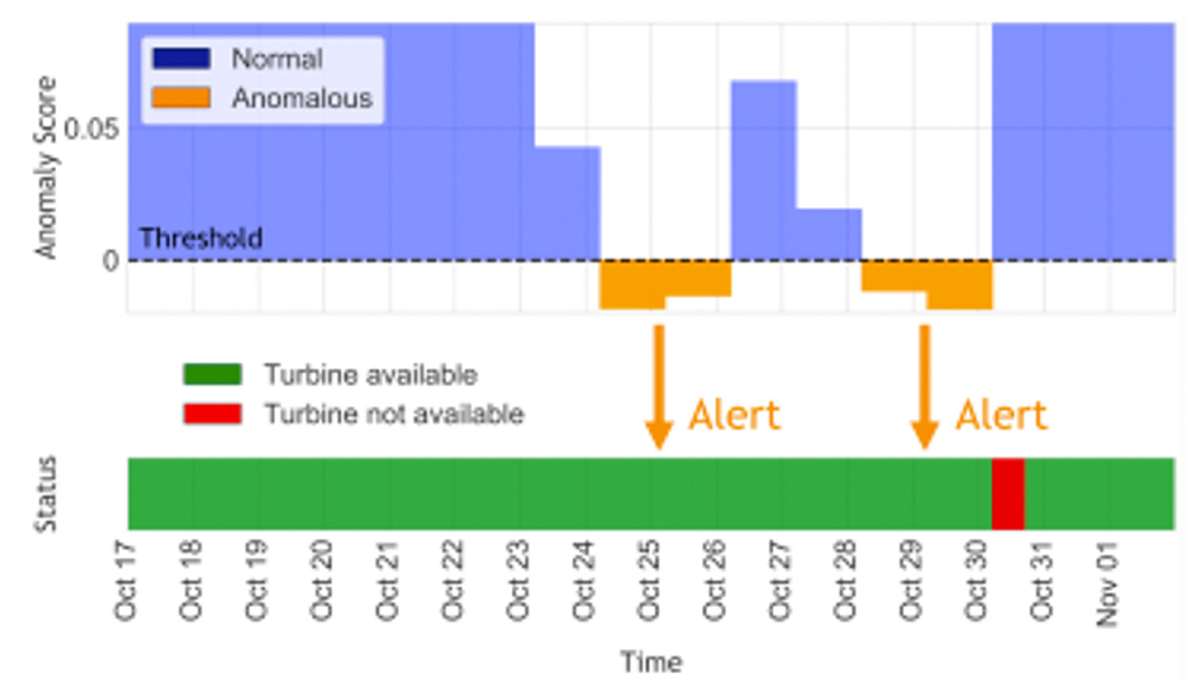

FIGURE 3: Example of fault detection on the test set.

For every alarm/warning that occurred in the three weeks preceding historical fault events, we extracted features (examples in Tab.1). Among all the extracted features, we select those with an increasing or decreasing trend for the model's training. We train a machine learning algorithm for unsupervised anomaly detection to recognize anomalous patterns of alarms and warnings. Fig. 3 illustrates an operational example of the model applied to an unseen "high gear box temperature" fault, showing that the model delivers an alert 5 days in advance of the fault.

Conclusions

Impact of AI-powered bidding optimization on storage asset revenue: The results of these analyses on a range of battery assets in California show that revenue uplift can be 40-50% compared to a manual bidding strategy and PoP to be 80-95%, with variations driven by asset size and configuration, warranty constraints, and location (i.e., pricing node). Not only does this mean that a 40-50% revenue increase is attainable by employing an algorithmic bidding solution, but also that just 5 - 20% of the theoretical maximum market revenue is left unaccounted for when using our powerful algorithmic trading platform.

Impact of AI-powered predictive maintenance analytics on renewable asset operational costs: The results of this example set of predictive maintenance analytics indicates that AI can produce significant cost savings for renewables asset owners by anticipating component failures and supporting advanced, planned maintenance over unplanned downtime. For example, for one customer this approach incorporated into a digital application identified a main bearing issue on a wind turbine over three months in advance of failure. If acted upon, this could have prevented six months of unplanned downtime. For this plant, that would have been 3.4 GWh over six months and translated to approximately $500,000 in saved costs.

In turn, digital applications that utilize AI can boost revenue and reduce costs from utility-scale renewables and storage assets, improving bottom-line and top-line financial performance for asset owners and operators. As portfolios scale, the value of these automated, advanced solutions only become more critical to profitability.

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