

Optimizing grid-scale battery operations

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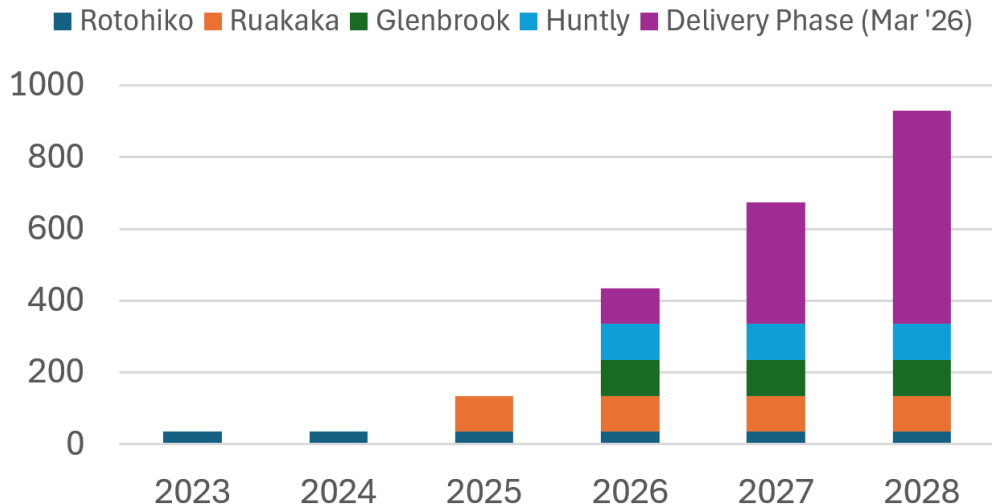
Joint work with Andy Philpott, Andrea Raith and Ramu Naidoo

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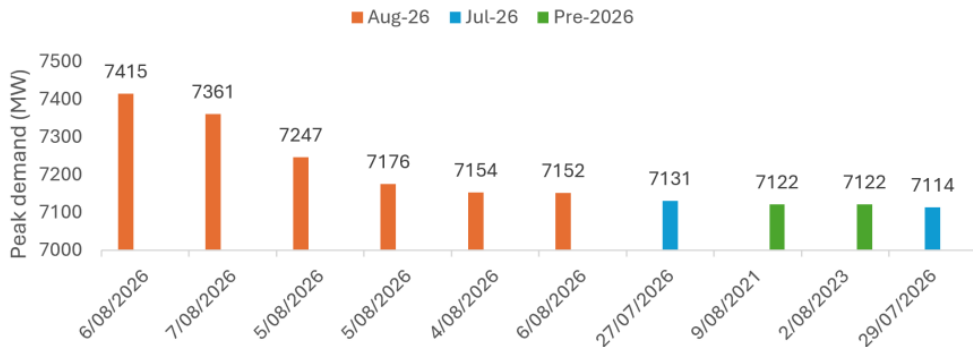
- ▶ Funded by MBIE
- ▶ Bridges the gap between industry and research
- ▶ Inaugural cohort: Energy
- ▶ 23 projects, 8 universities, 25 industrial partners

Expected Installed BESS Capacity



NZ's Battery Energy Storage System (BESS) future [<https://www.transpower.co.nz>]

Top 10 peaks in NZ electricity load

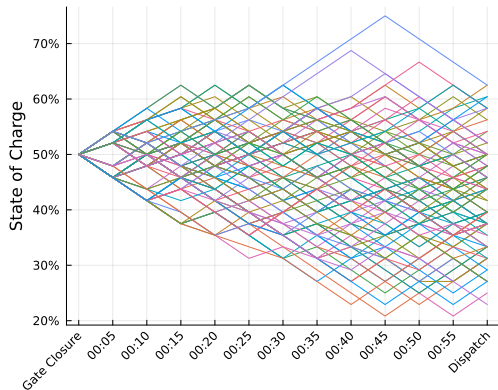
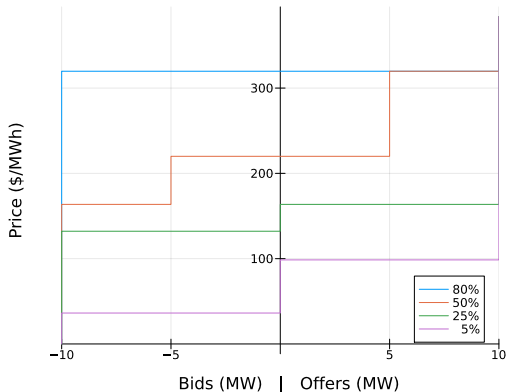


Recent demand spikes [<https://www.transpower.co.nz>]

Motivation: Research questions

- ▶ How should BESS operators trade to make the most of their assets?
- ▶ Does the current market set-up accommodate or *discourage* BESS?

Motivation: A closer look at BESS



- ▶ Similarly to Hydropower, the desired offer price depends on the storage level.
- ▶ The market requires all trades to be finalised 1 hour ahead of real-time dispatch.
- ▶ Conversely to Hydropower, regular operations during that hour can significantly and unpredictably change BESS storage level.

Potential solutions

Keep the dispatch
software as is and
tell BESS to
“deal with it”

Change the
dispatch software
to give special
treatment to BESS



Potential solutions

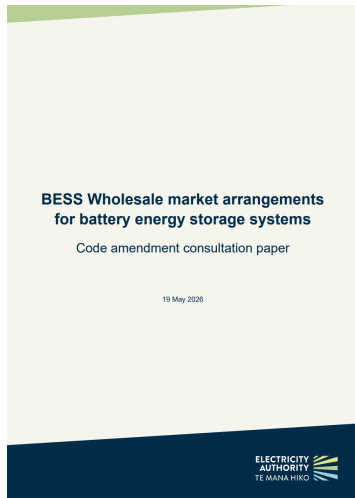
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Allow for offers and
bids to be dependent
on BESS State of
Charge

There is industry interest in such proposals!



Bid and offer prices should be linked to storage levels

- 6.47 NewPower proposed linking bid and offer prices to storage levels. This point was further explored in follow up meetings between the Authority and NewPower.

Recent Electricity Authority consultation on BESS [<https://www.ea.govt.nz>]

Battery Energy Storage Tool (BEST): Problem description

- ▶ Objective: maximize daily revenue for the BESS operator.
- ▶ BESS has a power and energy capacity P/E (MW/MWh).
- ▶ Days are split into 48 trading periods τ , and 288 “5-minute” real-time dispatch periods t .
- ▶ State of Charge (SoC) evolves over time y_t , where there is an optimal SoC (y_t^*) to end each period on.
- ▶ Optimal decision will depend on the time of day t , market price π_t and SoC at the beginning of the 5-min period/end of the previous 5-min period $\bar{y}_t = y_{t-1}$.

Battery Energy Storage Tool (BEST): Modelling price

- ▶ Prices are treated as a first order Markov process defined using all the historic data since real-time pricing came into effect.
- ▶ Prices are separated into price bands $\mathcal{B}$ indexed $1 : N$ of equal probability for each trading period τ .
- ▶ A probability transition matrix $M = \{m_{\tau,i,j}\}$ where $m_{\tau,i,j}$ is the probability of a 5-min period from trading period τ with the price in price band $\mathcal{B}_i$ being immediately followed by a 5-min period where the price was in price band $\mathcal{B}_j$.

Battery Energy Storage Tool (BEST): A dynamic program

- Recursively solve the following Bellman function:

$$V_t(\bar{y}_t, \pi_t) = \max_{y_t \in \mathcal{Y}(\bar{y}_t)} \left(\pi_t \times (\bar{y}_t - y_t) + Q(y_t, \pi_t) \right)$$
$$Q(y_t, \pi_t) = \sum_j m_{\tau,i,j} \times V_{t+1}(y_t, \mu_j)$$

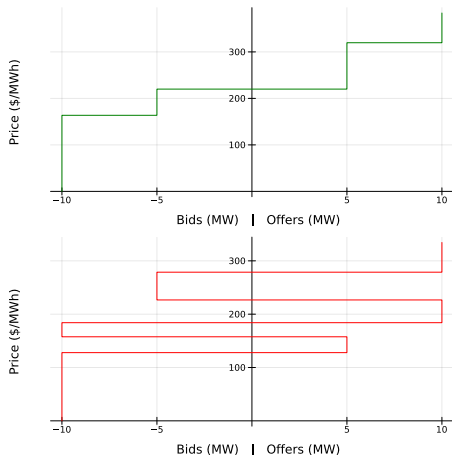
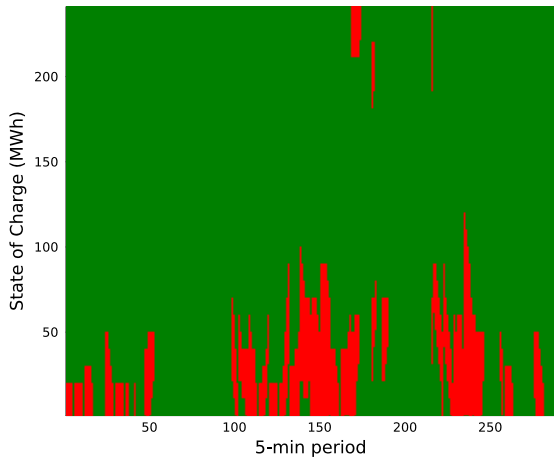
where $\pi_t \in \mathcal{B}_i$ and μ_j is the average price from $\mathcal{B}_j$ and

$$\mathcal{Y}(\bar{y}) = \{y : 0 \leq y \leq E, |y - \bar{y}| \leq P_{5min}\}$$

enumerates all feasible decisions.

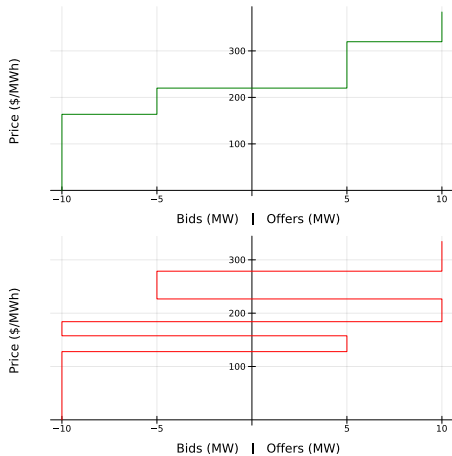
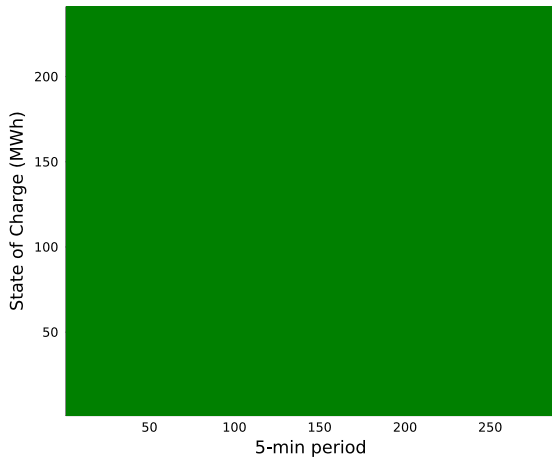
- Solving for $V_0(\cdot)$ finds the optimal SoC y_t^* for all possible combinations of $\bar{y}_t$ and π_t for all t throughout the day.

An interesting finding



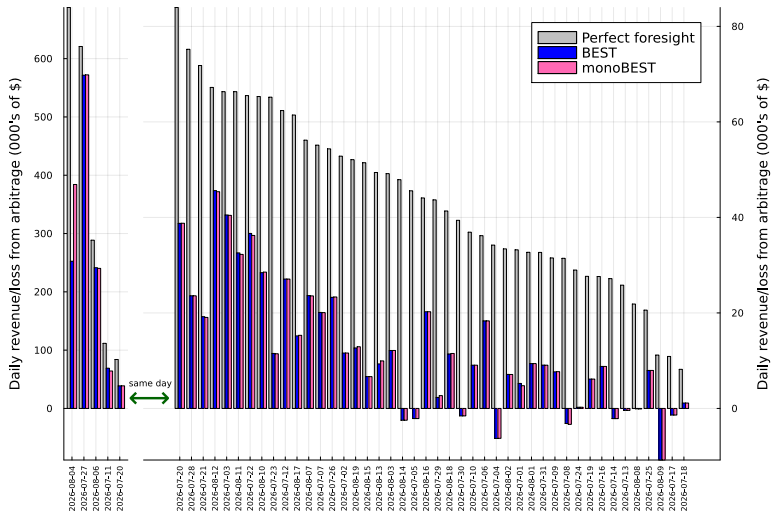
Situations in which optimal BEST policy is not monotonic w.r.t. price.

An interesting finding



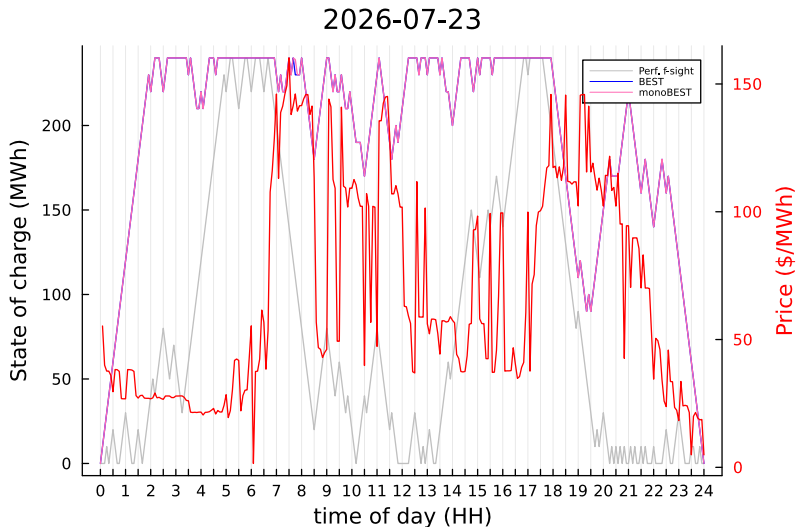
Situations in which optimal BEST policy is not monotonic w.r.t. price.

Results: Overview



Algorithm performance on days outside of the training set.

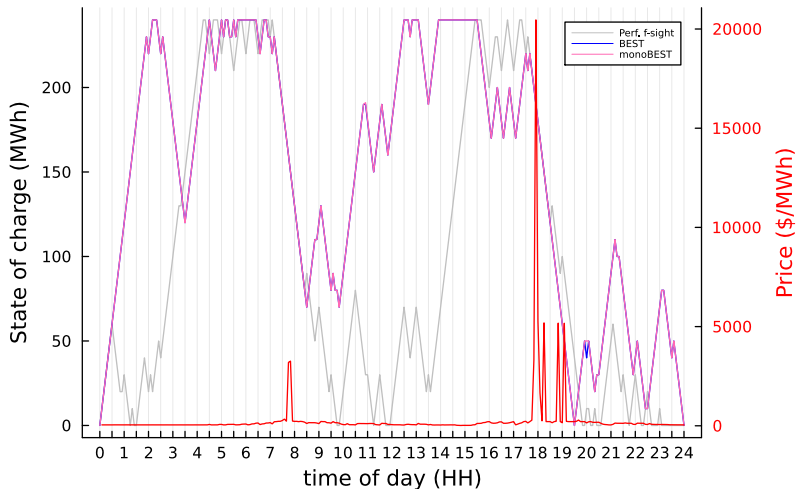
Results: A closer look



Trading decisions on a typical day.
Revenue = \$11,500 (17.5% of perfect foresight).

Results: A closer look

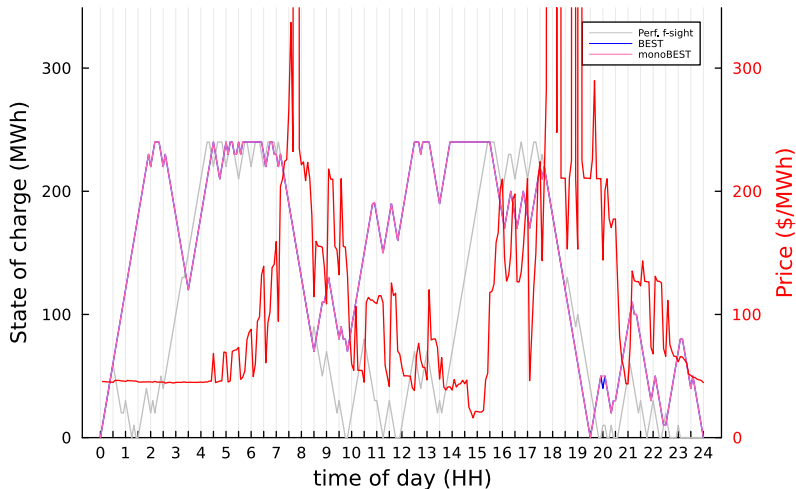
2026-07-27



Trading decisions on a “good” day.
Revenue = \$572,000 (92.0% of perfect foresight).

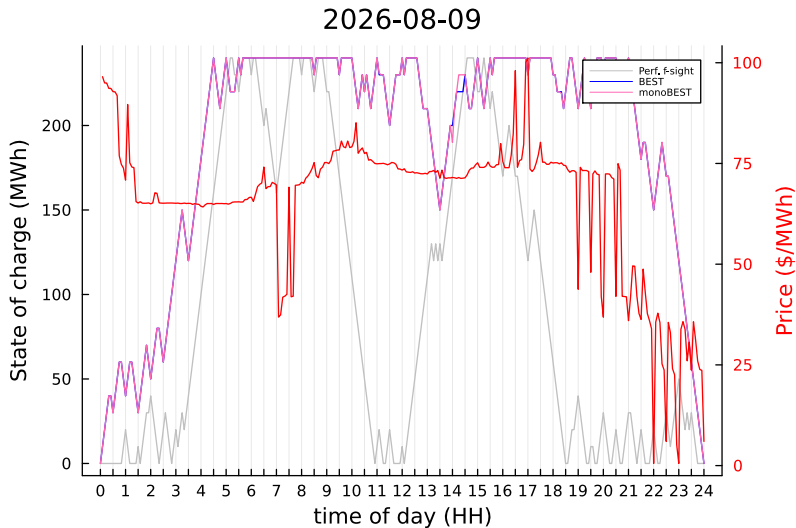
Results: A closer look

2026-07-27



Trading decisions on a “good” day.
Revenue = \$572,000 (92.0% of perfect foresight).

Results: A closer look



Trading decisions on a “bad” day.

Loss = \$10,800.

Where to next?

- ▶ This method shows promise, but how does it compare to the current market set-up?
- ▶ How to “plug in” this method to vSPD.
- ▶ Optimizing across multiple days: rolling horizon, end-of-day SoC valuations, etc.
- ▶ More accurate price-prediction mechanism.
- ▶ Incorporate other decisions: instantaneous reserves, ancillary services, BESS-Hybrid mechanisms, etc.

The End

Any questions?

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