Prediction-based Intraday Trading

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Motivation

Due to the increasing penetration of renewables in today's energy system, short-term trading platforms such as the intraday market are becoming more and more important. While there are numerous algorithms treating economic dispatch for simplified clearing mechanisms, only few methods that accurately represent the limit order book, e.g. [1] and [2], have been developed so far. However, none of the existing algorithms explicitly includes predictions. We fill this gap by proposing a modification of the myopic rolling intrinsic policy which uses the volume-weighted average price as a proxy to capture the expected revenue potential of the market.

Problem

How can predictions be utilized to optimize real-time intraday trading and dispatch of an arbitrary collection of assets?

Intraday Trading using Model Predictive Control

At each trading step t:

1. Read current order book → Price levels $\mathbf{P}^\pm_T$ and volumes $\mathbf{Q}^\pm_T$
2. Call prediction model → $\hat{P}_T$
3. Solve Eq. (2) → Control signal $\mathbf{q}^\pm_T$ and future decisions $v^\pm_T$
4. Submit $\mathbf{q}^\pm_T$ to market
5. Update dispatch schedule using clearing results

Clearing Open Positions

$v^\pm_T$ represents open positions, if they are not cleared before gate closure, the physical constraints $\mathbf{x} \in \mathcal{X}$ may be violated!

→ Limit the open volume per product using a function $V(\Delta t)$ of the remaining time to delivery Δt.

Example Function

$$V(\Delta t) = 1\,\mathrm{MW\,h} \times \Theta(\Delta t - 30\,\mathrm{min}) \tag{1}$$

Interpretation: At each trading step, at most 1 MW h may be "spent" on predicted prices per product. 30 min before delivery, the remaining open position must be cleared.

Optimization Model

$$\begin{aligned}
&\max_{\mathbf{q}^\pm_T, v^\pm_T, \mathbf{x}} \sum_{T=1}^{\mathcal{T}} \left(\mathbf{P}^-_T \cdot \mathbf{q}^-_T - \mathbf{P}^+_T \cdot \mathbf{q}^+_T\right) + \sum_{T=1}^{h} \hat{P}_T \left(v^-_T - v^+_T\right) \\
&\sum_{l \in \mathcal{O}^+_T} q^{+,l}_T - \sum_{l \in \mathcal{O}^-_T} q^{-,l}_T + v^+_T - v^-_T = D_T(\mathbf{x} \in \mathcal{X}) \quad T = 1, 2, \ldots, h \\
&\sum_{l \in \mathcal{O}^+_T} q^{+,l}_T - \sum_{l \in \mathcal{O}^-_T} q^{-,l}_T = D_T(\mathbf{x} \in \mathcal{X}) \quad T = h+1, h+2, \ldots, \mathcal{T} \\
&0 \le \mathbf{q}^\pm_T \le \mathbf{Q}^\pm_T \quad T = 1, 2, \ldots, \mathcal{T} \\
&0 \le v^\pm_T \le V(T - t) \quad T = 1, 2, \ldots, h
\end{aligned} \tag{2}$$

Case Study: Battery Operation in Austria

Goal: Use true ID3 to quantify the potential benefit for various prediction horizons h.

Parameters:

- Max. state of charge: 10 MW h
- Min./Max. power: ±3 MW
- Trading frequency: 60 s
- Buffer function: Eq. (1)
- 4 weeks in 2023
- Only hourly products

Results: Battery Operation in Austria

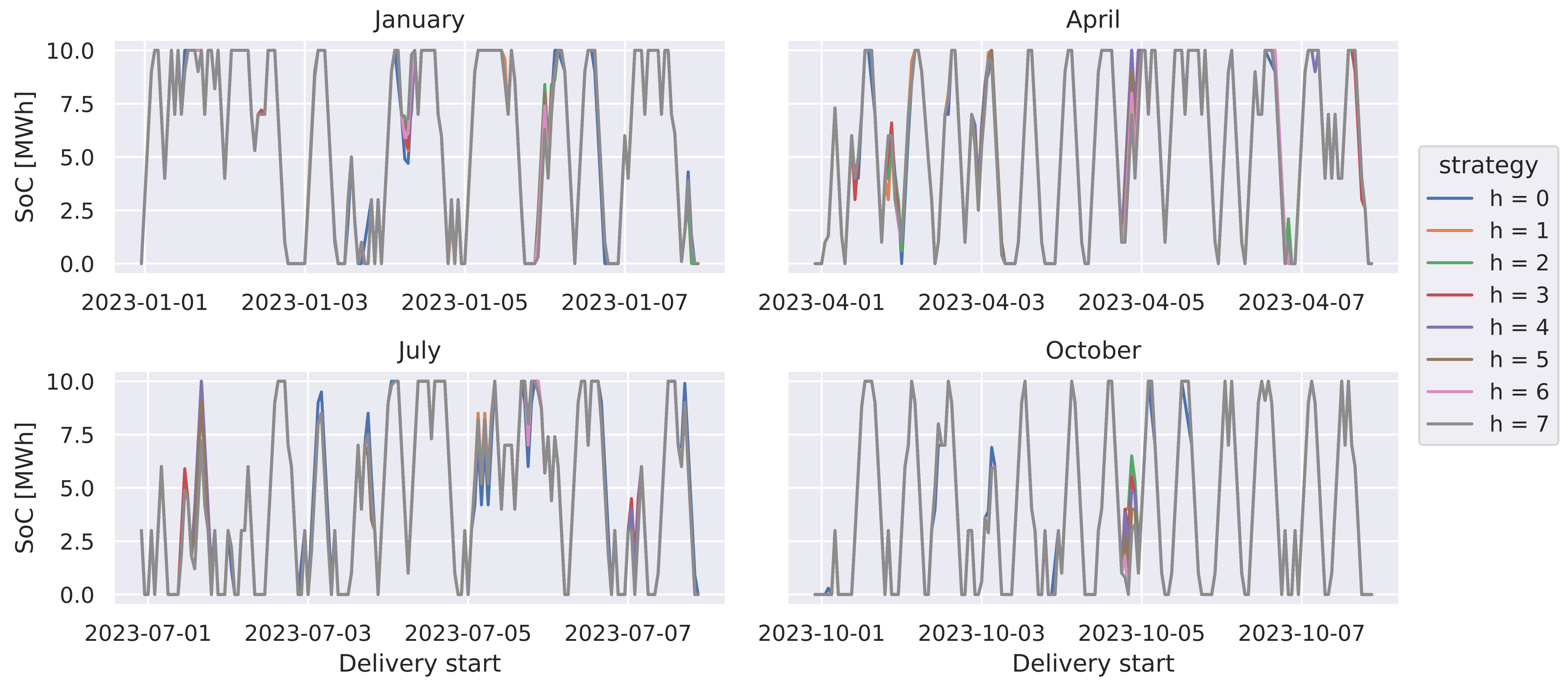

Figure: Final battery schedule.

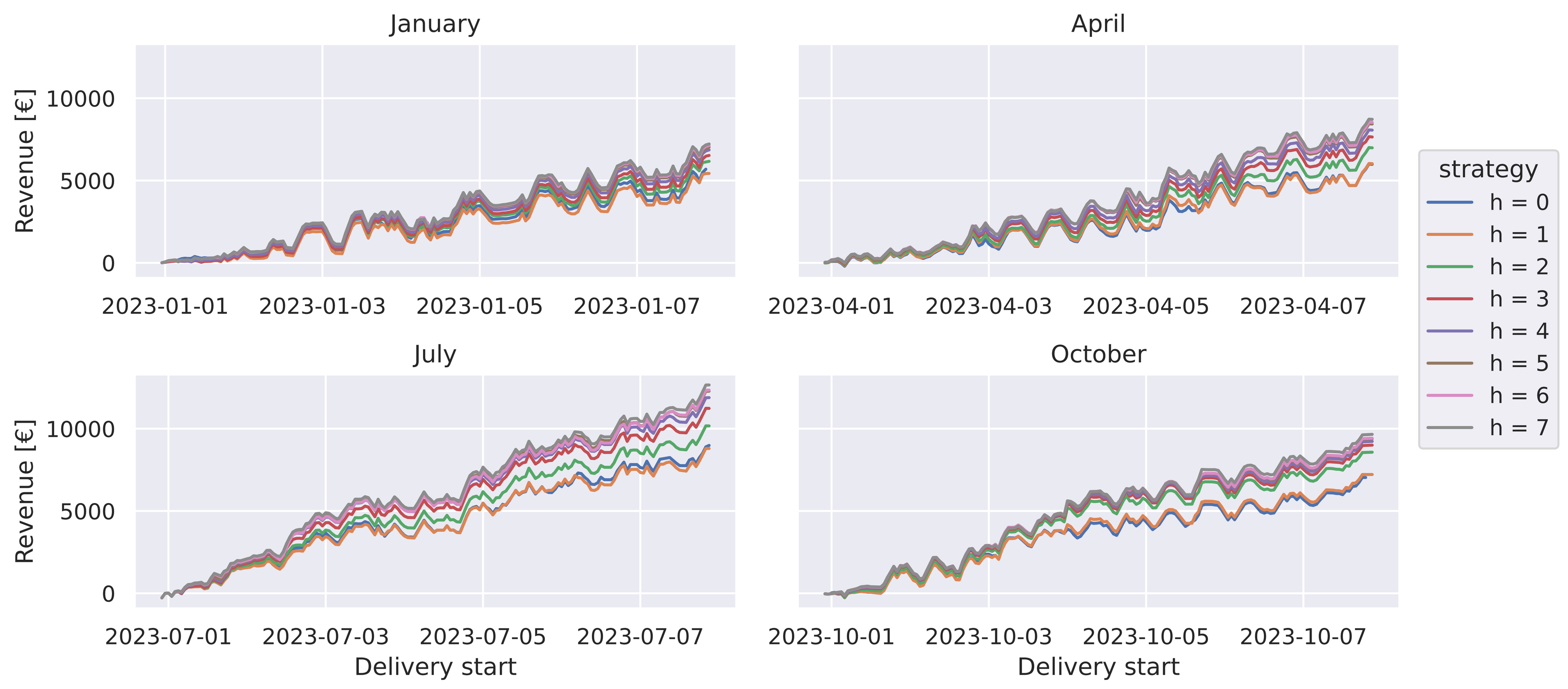

Figure: Cumulative revenue against delivery start.

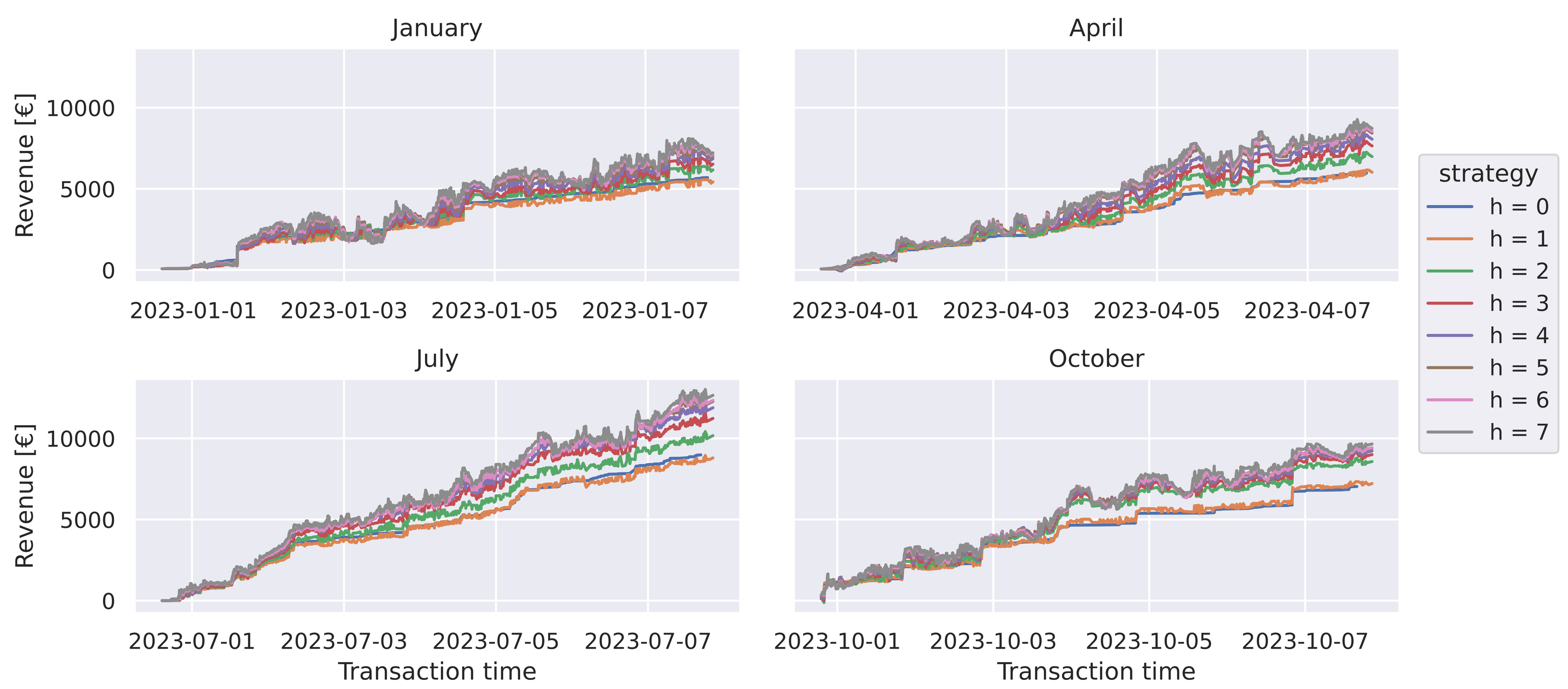

Figure: Cumulative revenue against real time.

Conclusion

- ID3 is a valid proxy and offers a trading edge on the market.
- Increasing the prediction horizon leads to varying levels of benefit.
- The physical battery schedule depends only weakly on the prediction horizon.

Outlook

- Add noise and use real predictions
- Test against other proxies, e.g. median price
- Probabilistic forecasts → risk quantification
- Market coupling and imbalance penalties
- Uncertain demand and generation

References

[1] I. Boukas et al., "A deep reinforcement learning framework for continuous intraday market bidding," *Machine Learning*, vol. 110, no. 9, pp. 2335–2387, Sep. 1, 2021. DOI: 10.1007/s10994-021-06020-8

[2] G. Bertrand and A. Papavasiliou, "Adaptive Trading in Continuous Intraday Electricity Markets for a Storage Unit," *IEEE Transactions on Power Systems*, vol. 35, no. 3, pp. 2339–2350, May 2020. DOI: 10.1109/TPWRS.2019.2957246