Algorithmic Power Trading Challenges and Weather Based Strategies

T. Kuppelwieser, N. Löhndorf, D. Wozabal

Seminar Series Energy & Finance, 05/2021

Outline

1. Coordinated day-ahead and intraday market bidding
2. Weather based trading strategies on intraday markets
3. Liquidity of intraday markets

Outline

N. Löhndorf, D. Wozabal. *The Value of Coordination in Multimarket Bidding of Grid Energy Storage*. Working Paper, 2021.

T. Kuppelwieser, D. Wozabal. *Intraday Power Trading: Towards an Arms Race in Weather Forecasting?*. Working Paper, 2021.

T. Kuppelwieser, D. Wozabal. *Liquidity Costs on Intraday Power Markets: Continuous Trading Versus Auctions*. Energy Policy, 2021.

Motivation

Goal

Optimal non-anticipative trading strategies on short-term markets.

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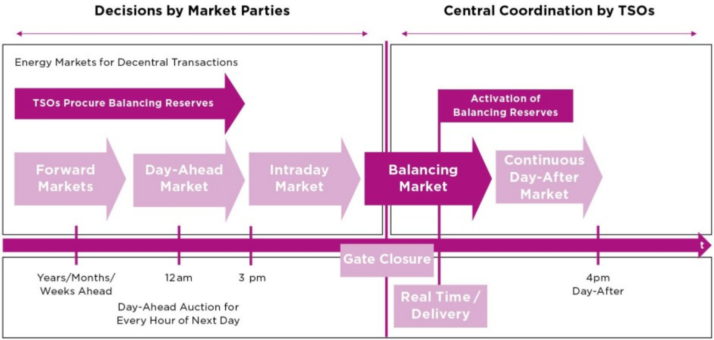
We deal with the following setting

- European market design
- No long-term future markets
- No bidding on reserve markets
- Special focus on continuous intraday trading
- Take perspective of single players that
  - are not acting strategically
  - recognize that the market is not efficient

Short-Term Power Markets

- Day-ahead market: auction one day ahead of delivery
- Intraday market: continuous, trades until shortly before delivery
- Balancing market
  - auction one day before delivery
  - remuneration for power and energy
  - continuous calls-offs by the TSO



Decisions: Problems & Complications

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- Demands and production are random

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- Products *seize to exist* (electricity is a *service*)

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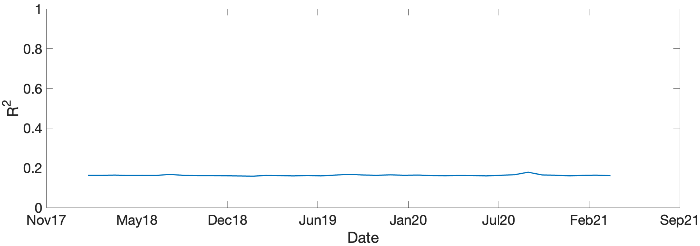
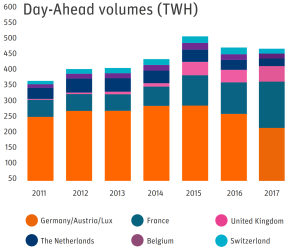
- Hard technical constraints, demands have to be fulfilled
- High temporal resolution
- Products *seize to exist* (electricity is a *service*)
- Illiquid markets
- Interaction between markets is non-trivial
    - Market prices often do not reflect true values

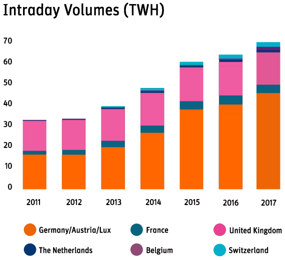
$$\text{reBAP}_t = \beta_0 + \beta_1 \text{ID1}_t + \varepsilon_t$$



Liquidity

- Day-ahead market: high volumes, auction
- Intraday: smaller volumes, trading *spread out*





Source: EPEX, 2018

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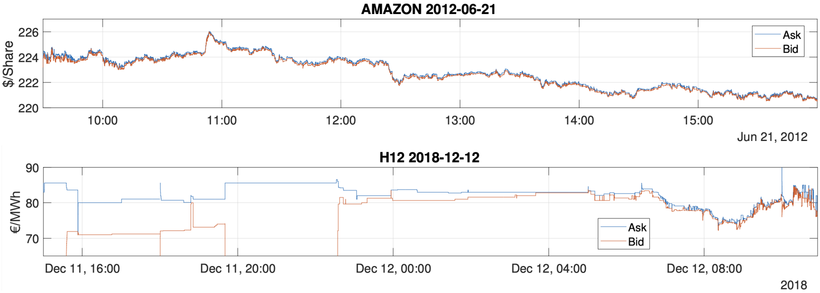
- Liquidity costs on intraday markets are still substantial



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Volume Weighted Cost of Roundtrip per MWh (17.11.2017 to 15.06.2018)

Subset	N	mean	std	min	25%	50%	75%	max
0.1MWh	4991	1.99	1.23	0.55	1.24	1.64	2.34	14.32
5MWh	4991	2.20	1.33	0.62	1.40	1.83	2.60	24.31
10MWh	4991	2.38	1.42	0.72	1.54	1.99	2.79	35.52
15MWh	4991	2.56	1.49	0.81	1.69	2.17	3.00	39.55
50MWh	4991	3.90	2.09	1.32	2.67	3.37	4.52	58.61

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- Liquidity costs on intraday markets are still substantial
- Continuous trading tends to increase (liquidity) cost
  - Schwartz (2012)
  - Budish et al. (2015)
  - Du and Zhu (2017)
  - Deutsche Börse Group (2018)

Day-Ahead & Intraday: The Value of Coordination

Setting

Market an energy storage on the day-ahead and intraday market.

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Question I

Why not exclusively trade on the day-ahead market?

Question II

Why not exclusively trade on the intraday market?

Question III

Why not trade trade on both markets and decide independently?

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Day and Intraday: A Simple Model

Assumptions

- Maximize expected profits of an electricity storage
- Bid for two time periods
  - t = 0: Bid on day-ahead market for delivery in $t = 1, 2$
  - t = 1: Intraday market trading for period 1
  - t = 2: Intraday market trading for period 2
- Start with empty storage
- Linear price response β for intraday market trading
- No price response for day-ahead trading
- $\mathbb{E}(P_t^I | P_t^D = p_t^D) = p_t^D$ for $t = 1, 2$

Day and Intraday: A Simple Model

Proposition

If intraday prices have a higher *dispersion*, then

- it is never optimal to use full capacity on the day-ahead market;
- there exists $\bar{\beta} > 0$ such that for $\beta \in [0, \bar{\beta}]$, it is optimal to only trade on the intraday market.

- Attractiveness of the intraday market: volatility & information
- Attractiveness of the day-ahead market: market depth
- Small and fast storages should focus on the intraday market
- Larger storages should focus on the day-ahead market

Value of Coordination: Case Study

- Day-ahead trading
- Hourly intraday trading
- Fit price processes from data (order book) data
- Calculate LB on value of coordination using scenario trees
- UB by information relaxation
- Three types of assets
  - Small battery storage: 10MW / 10 MWh, efficiency of 95%
  - Pumped hydro storage: 1000 MW / 8000 MWh, efficiency of 75%
  - Seasonal hydro: 100 MW, no pump, 50 MW continuous inflow

Numerical Results

	Season	Market	Avg Profit (EUR) ID	Avg Profit (EUR) Sequential	Avg Profit (EUR) Coordinated	Avg Volume (MWh) ID	Avg Volume (MWh) Sequential	Avg Volume (MWh) Coordinated
Pumped Hydro	Summer	DA	0	25,448	-24,554	0	12,250	11,488
		ID	37,724	24,725	88,756	14,222	10,476	11,229
		Both	37,724	50,173	64,202	14,222	22,726	22,717
	Winter	DA	0	129,033	77,834	0	16,917	15,518
		ID	94,027	25,732	89,822	21,506	8,872	9,018
		Both	94,027	154,764	167,656	21,506	25,788	24,536
Battery	Summer	DA	0	292	171	0	41	38
		ID	506	252	405	316	272	149
		Both	506	544	576	316	313	187
	Winter	DA	0	391	161	0	41	35
		ID	785	411	687	331	307	158
		Both	785	801	848	331	348	192
Reservoir	Summer	DA	0	48,038	46,881	0	1,200	1,200
		ID	35,728	1,544	3,449	3,046	1,084	1,072
		Both	35,728	49,582	50,329	3,046	2,284	2,272
	Winter	DA	0	68,478	67,032	0	1,200	1,200
		ID	49,983	1,471	3,093	2,716	728	666
		Both	49,983	69,948	70,125	2,716	1,928	1,866

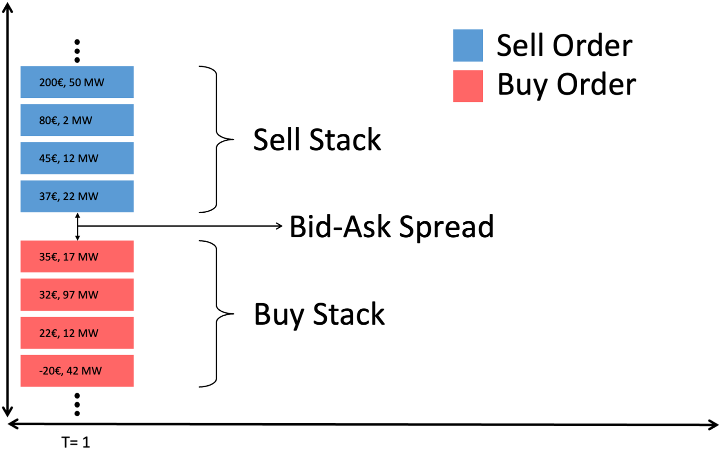
Problem with Decisions

Challenge

Finding (globally) optimal intraday trading strategies is hard!

- Decisions are single buy and sell decisions for a random price
  - Intraday market: continuous trading based on a limit order book
- Order book dynamics
  - evolve at short time scale
  - changes happen at random points in time
  - order book consists of bid and offer *curves*
- Need another layer of modeling to make trading decisions

Order Book Dynamics



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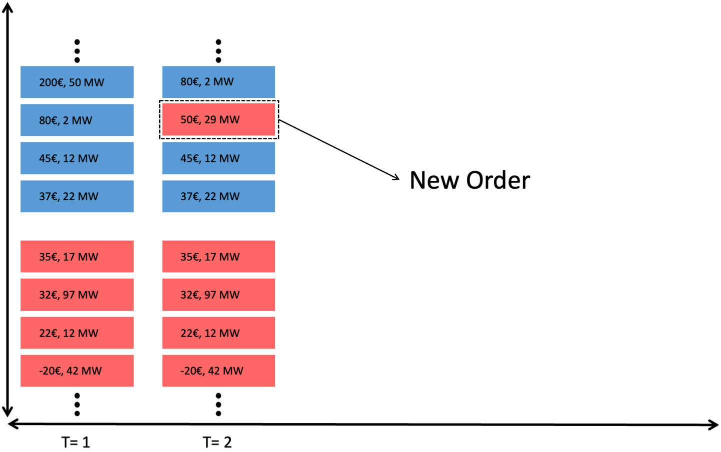

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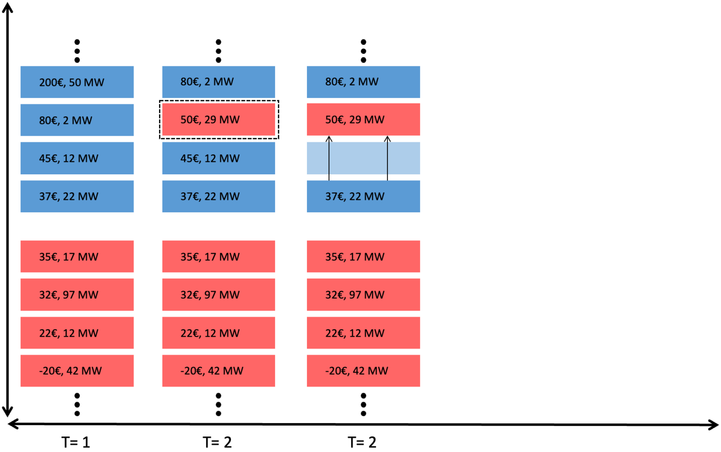

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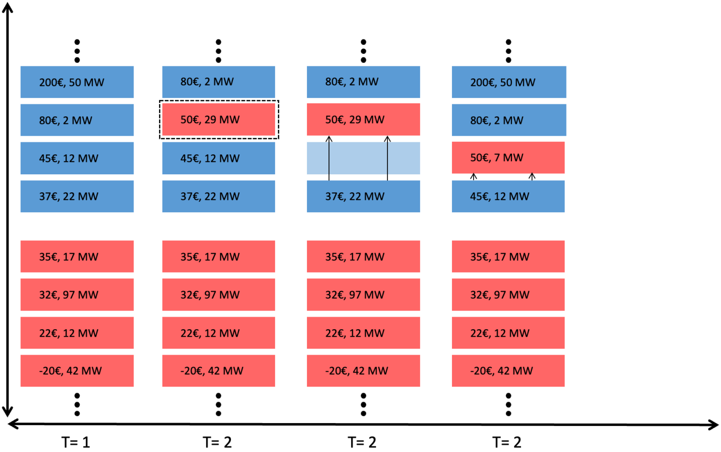

Order Book Dynamics

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Non-anticipative trading strategy for intraday-only *arbitrage trading*.

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Non-anticipative trading strategy for intraday-only *arbitrage trading*.

- No assets, no demand
- Accurate processing of order level data
- Policy should prescribe directly implementable trading decisions
- Decision should be computable in real time
- Positive *out-of-sample profits*

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Non-anticipative trading strategy for intraday-only *arbitrage trading*.

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Intraday Trading: Literature

- Most papers on intraday trading consider asset backed trading
- Most papers do not consider exact order book dynamics
  - Exception: Bertrand and Papavasiliou (2019)
- Some related recent literature
  - Kath and Ziel (2018): Day-ahead vs intraday based on forecasts
  - Maciejowska et al. (2019): Day-ahead vs intraday arbitrage
  - Bertrand and Papavasiliou (2019): Storage optimization
  - Monteiro et al. (2020): Arbitrage trading with futures
  - Wozabal and Rameseder (2020): Auction based intraday trading
  - Kath and Ziel (2020): Optimal order execution

Interlude: Milliseconds & Microwaves

High frequency trading on financial markets (Budish et al., 2015).

- Trading on *signals* indicating changes in asset values
- The proceeds of HFT strategies go to fastest trader
- *Arms race for speed*

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Ping Time New York-Chicago

- Telecommunication line between NY and Chicago: 16 *ms*
- *Spread Networks*. *Straight* cable for $300 Mio.: 13 *ms*
- Since then: microwave towers reducing time to 8 *ms*
- Speed limit: 4 *ms* (speed of light)

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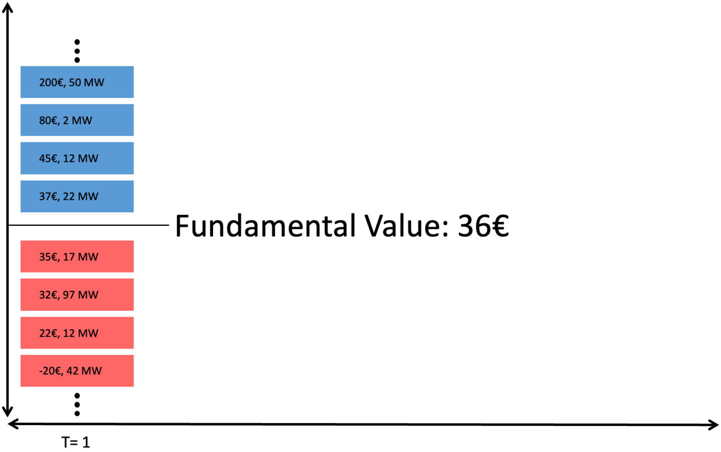
- Similar races take place in other areas
  - Computing: code held in the L1-cache of processors
  - Ping times within the exchange: distance to clearing server
- Earnings from ES vs SPY arbitrage alone: $75 Mio/year

Sniping Stale Quotes



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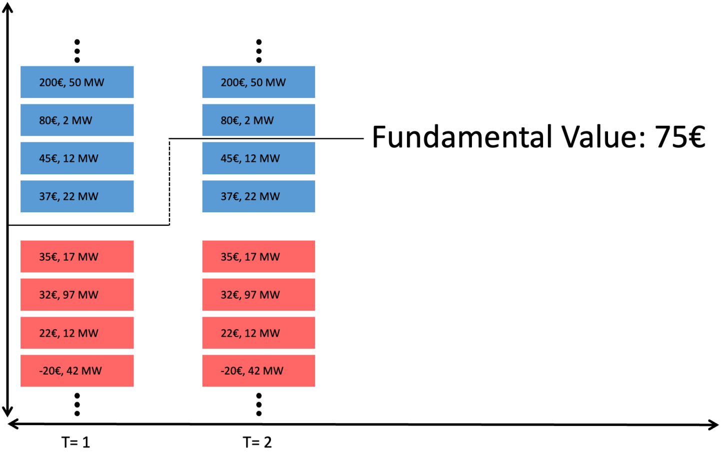

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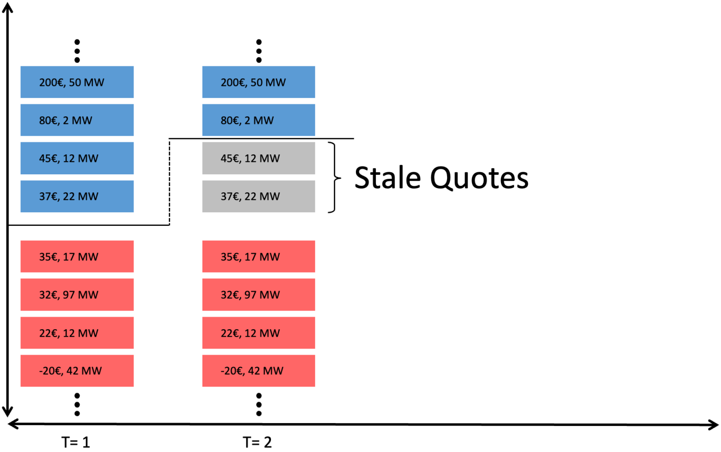

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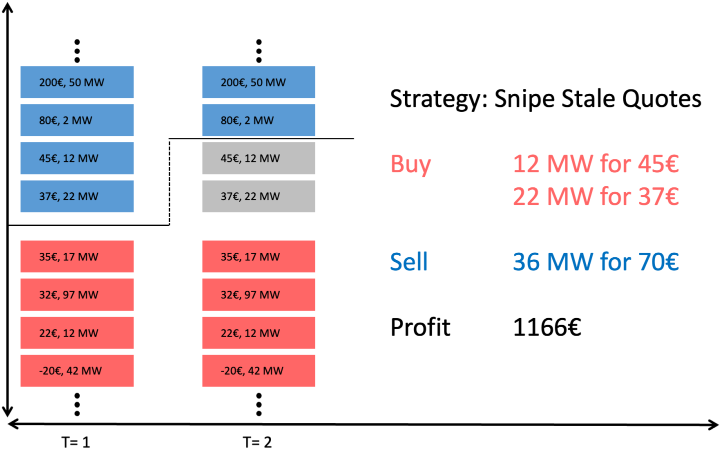

Strategy: Snipe Stale Quotes

Buy	12 MW for 45€ 22 MW for 37€
Sell	36 MW for 70€
Profit	1166€

Trading Strategy: Intuition

Renewables and intraday prices

- German market has a significant fraction of renewable energy
- Day-ahead market trading based day-ahead weather forecasts
- Forecast errors trigger supply/demand shocks and price changes at the intraday market
  - Kiesel and Paraschiv (2017)
  - Kremer et al. (2020a,b)
  - Kulakov and Ziel (2019)

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Strategy

Trade based on superior (early) forecasts of *day-ahead forecast errors* anticipating future intraday price changes.

Weather Forecasting

Traditional Weather Forecasting

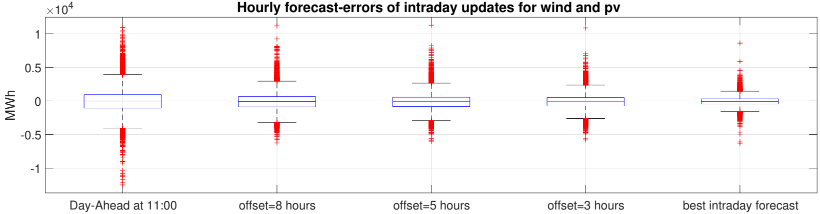
Traditional weather forecasting produces infrequent forecasts with a coarse temporal resolution.

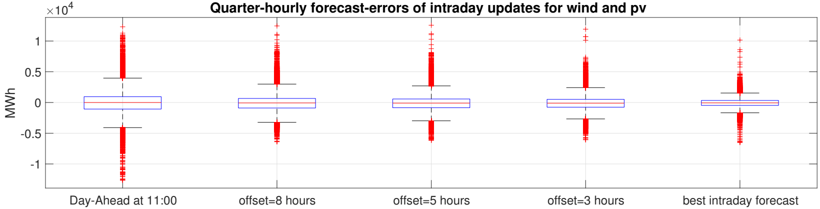
- Based on *expensive* data (satellite images, weather balloons)
- Only 4 – 6 updates a day

VRES expansion prompted the development of specialized forecasts

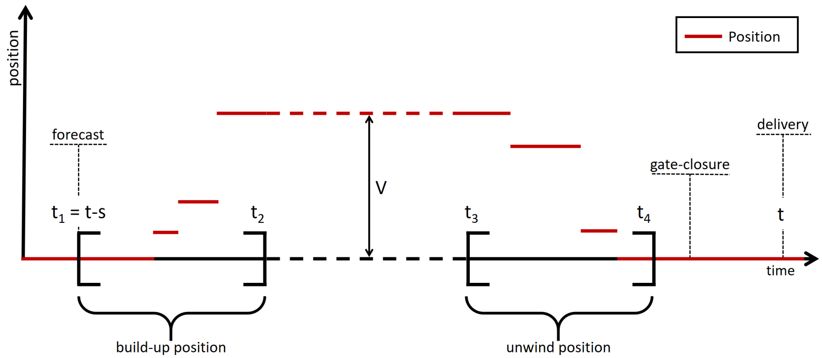
- Feedback from real time production data
- Forecasting relevant parameters (wind speeds, cloud cover)
- New providers
  - Enfor, ConWX, Gnarum, enercast, weathernews, windsim, Meteologica

Forecasts: VRES Production





A Parametric Policy

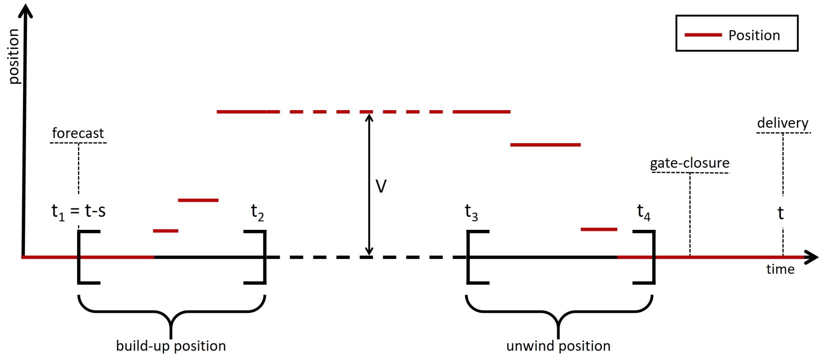


- Trade contract with delivery at t based on forecast from $s < t$

$$\varepsilon_t^s = f_t^{DA} - f_t^s$$

- Trade (up to) quantity V
- Build up position in $[t_1, t_2]$ and unwind in $[t_3, t_4]$

A Parametric Policy (contd.)



- Define a thresholds Δ^+ and Δ^- for *signal strength*
- Calculate trading decision x_{t_1} as

$$x_{t_1} = \begin{cases} V^+, & \text{if } \varepsilon_t^s > \Delta^+ \\ -V^-, & \text{if } \varepsilon_t^s < -\Delta^- \\ 0, & \text{otherwise.} \end{cases}$$

Patience is key?

Modes of Trading

Two ways of interfacing with the continuous market:

1. Accepting existing limit orders
2. Placing limit/market orders

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Impatient Strategy

- Build up position with *immediate-or-cancel* market order at t_1
- Unwind position with *immediate-or-cancel* market order at t_4
- Clear imbalance for reBAP

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Patient Strategy

- Build up position placing limit order on top of bid/offer stack at t_1
- Make sure that order stays on the top until either V is traded or t_2
- Unwind position in the same manner in $[t_3, t_4]$
- *Immediate-or-cancel* market order at t_4 for remaining position
- Clear imbalance for reBAP

Optimizing the Strategy

Parameter Choice

Fix timing and use a simple grid search on a discrete policy space.

Fix timing

- Use forecast 8 hours before delivery and choose $t_1 = t - 8\text{h}$
  - 8 hour forecast allows to react early
- $t_2 = t - 3\text{h}$, i.e., we choose a long first trading period
  - Ensures enough time to build up position, when liquidity is limited
- Choose $[t_3, t_4] = [t - 65\text{m}, t - 35\text{m}]$ to unwind the position
  - Better liquidity close to delivery
  - 5 remaining minutes used for market orders to close positions (patient strategy)

Optimizing the Strategy

Parameter Choice

Fix timing and use a simple grid search on a discrete policy space.

Grid search to determine $V^\pm$ and $\Delta^\pm$

- Using historical training data on days $d \in \mathcal{D}_1$
- Define set of thresholds $\mathcal{L} = \{100 \cdot i : \ 0 \leq i \leq 20\} \subseteq \mathbb{N}$
- Define set of volumes

$$\mathcal{V} = \{1, 5\} \cup \{10 \cdot i : \ 1 \leq i \leq 30\} \subseteq \mathbb{N} \qquad \text{for hourly products}$$

$$\mathcal{V} = \{1, 2, 3, 4\} \cup \{5 \cdot i : \ 1 \leq i \leq 6\} \subseteq \mathbb{N} \quad \text{for } {}^1\!/_4\text{-hourly products}$$

- Define $\Pi_d(\Delta^\pm, V^\pm)$ as trading profits on day d and solve

$$(\bar{\Delta}^\pm, \bar{V}^\pm) \in \arg\max \left\{ \sum_{d \in \mathcal{D}_1} \Pi_d(\Delta^\pm, V^\pm) : V^\pm \in \mathcal{V}, \ \Delta^\pm \in \mathcal{L} \right\}.$$

In-Sample Evaluation

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  - 58.6 million orders for hourly products
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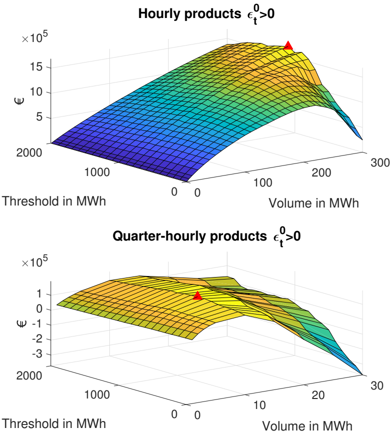
- Test *patient trading* strategy against *impatient strategy*
- Define a sensible range for parameter values

Results

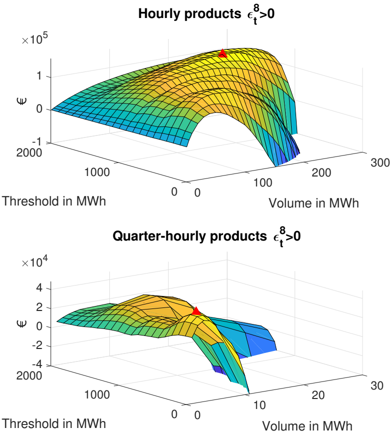
			Positive			Negative			Overall
			Profit	V^+	Δ^+	Profit	V^-	Δ^-	Profit
Actual (ε_t^0)	Patient	QH	192 659	10	700	214 774	10	300	407 433
		H	1 686 492	300	1 100	1 560 323	270	1 000	3 246 816
	Impatient	QH	-48 892	1	2 000	-17 350	1	2 000	-66 242
		H	65 167	20	2 000	3 684	1	1 600	68 852
Forecast (ε_t^8)	Patient	QH	48 438	4	200	52 589	4	0	101 027
		H	157 222	200	1 200	331 196	270	1 000	488 418
	Impatient	QH	-30 937	1	2 000	-3 766	1	2 000	-34 703
		H	168	1	1 600	5 607	20	2 000	5 775

- Patient strategy clearly outperforms impatient strategy
- ε_t^0 generates 5-10 more profits than ε_t^8
- QH products permit less volume and generate less profit

Optimal Parameters (ε_t^0)



Optimal Parameters (ε_t^8)



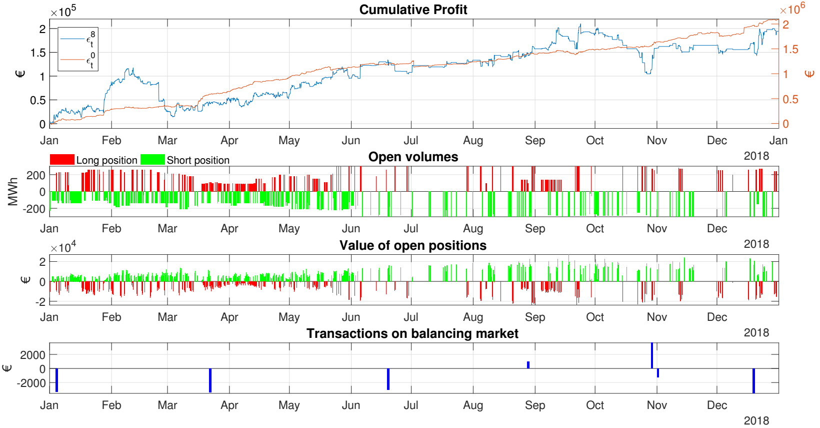
Out-of-Sample

Goal

Train non-anticipative strategy.

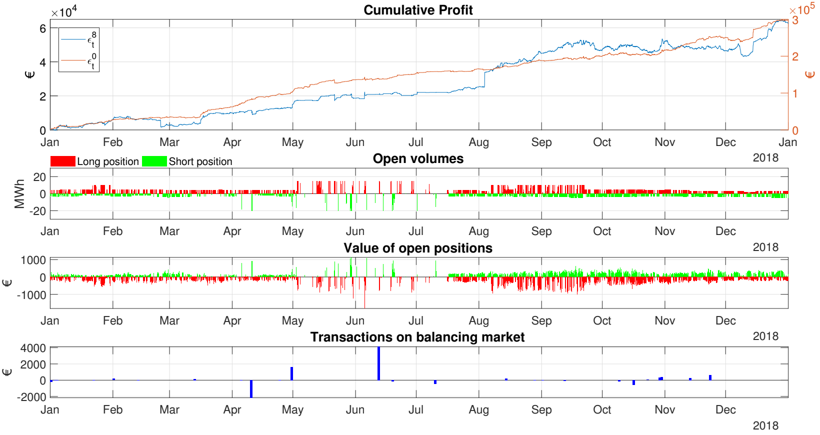
- Evaluation period: 01.01.2018 until 31.12.2018
- Results for ε_t^0 and ε_t^8
- Only test patient strategy
- Rolling window setting
  - Retrain strategy every day based on the last 180 days of data
- Evaluate on detailed order book data
- Take transaction costs into account

Out-of-Sample: Hourly Products



- True forecast yield profits one order of magnitude larger
- Profits positive overall, but many products with losses
- Large volumes are being traded

Out-of-Sample: Quarter Hourly Products



- Smaller volumes and open positions
- Less volatility in daily profits

Out-of-Sample: Statistics

	Hour		Quarter Hour	
	ε_t^8	ε_t^0	ε_t^8	ε_t^0
Profit	194 385	2 087 823	62 724	297 656
Balancing Costs	-9 865	31 202	4 214	8 055
Mean	22.29	239.43	1.8	8.52
Standard Deviation	968	2 110	44	99
p-value of t-test	0.0316	0.0000	0.0000	0.0000
Minimum	-21 220	-93 030	-1 731	-2 717
1% quantile	-2 814	-3 740	-98	-246
10% quantile	-394	-929	-22	-30
Median	0	0	0	0
90% quantile	522	1824	28	69
99% quantile	3 137	5 600	118	300
Maximum	15 908	32 174	1 836	3 518
Number of products	8 288	8 288	33 189	33 187
Number of traded products	2 853	4 732	21 425	21 044
Number of individual trades	136 863	311 802	223 593	367 719

- Profit for hourly products larger than for quarter hourly products
- Profits for perfect forecast 5-10 larger than for ε_t^8

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- No significant balancing costs

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- All profits are significantly positive

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- Higher *risk* (dispersion) for ε_t^0 and for hourly products

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- Only a fraction of products is actually traded
- Strategy generates a substantial amount of limit orders

Conclusion

- Coordination between day-ahead and intraday markets
  - Coordinated bidding is optimal
  - Finding optimal trading decisions is hard

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- Profitable weather based trading strategies exist
  - Intraday market is not (semi)-strong efficient
  - Potential for considerable improvement with better forecasts
  - Potential for better strategies
  - Potential for more sophisticated learning

Conclusion

- Coordination between day-ahead and intraday markets
  - Coordinated bidding is optimal
  - Finding optimal trading decisions is hard
- Profitable weather based trading strategies exist
  - Intraday market is not (semi)-strong efficient
  - Potential for considerable improvement with better forecasts
  - Potential for better strategies
  - Potential for more sophisticated learning
- Liquidity cost on the intraday market is substantial
  - Impatient strategies based on market orders are unprofitable
  - Day-ahead market is still attractive

david wozabal
david.wozabal@tum.de

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Capital Requirements (Insample)

			Mean	Max	Min	Std
Hour	Patient	ε_t^8	-22 163	5798	-210 712	40 655
		ε_t^0	-57 795	117 889	-38 7446	75 280
	Impatient	ε_t^8	-68	0	-1015	159
		ε_t^0	-2 246	5277	-23 798	4 015
QH	Patient	ε_t^8	404	21 450	-24 865	6 256
		ε_t^0	1 597	49 375	-33 657	10 711
	Impatient	ε_t^8	-141	2 613	-19 710	1 047
		ε_t^0	-276	4 069	-10 835	1 424