The value of e-mobility flexibility for aggregators – Portfolio management and contract design based on price and quantity uncertainty

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Motivation, Relevance and Research Question

Motivation

- Climate mitigation targets foster the deployment of electric vehicles.
- Even though much discussed in research, vehicle flexibility is rarely used until today.
- The role of flexibility aggregators is recently gaining traction.
- End consumers must see a benefit to offer flexibility. → Retail contract design is crucial.
- Technical hurdles exist, but end-consumer and aggregator perspectives are important.

Research Questions

- To what extent do contract specifications drive the overall financial performance?
  - Minimum filling level requirements
  - Different hours

Outline

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Motivation and Relevance:

Method:
Least Square Monte Charlo Valuation

Data:
Mobility & Price Expectations

Preliminary Results of Varying Contracts

Conclusion and Outlook

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Least Square Monte Carlo Simulation

- Approach for **real option valuation**
  - The stochastic method considers different future price trajectories.
  - Originally applied to the value of an American option (that can be exercised in any future timestep)

- **Dynamic programming approach:**
  Decision making within each timestep for a certain time horizon is considered.
  - Use of **price forecasts** and **operational limitations** of the asset i.e., filling level and (dis)charging limitations
  - **Backward induction**: From the last known information (the furthest in the future) optimal decisions are computed and then this information is used for the previous timestep, iterating until the issue time.
  - **Forward simulation:** Consider the realization of this timestep and repeat for the next timestep.

- **Ex post financial analysis:** After computing the best strategy for each timestep and filling level, the storage (dis)charge schedule and financial performance can be derived in the end.

Model extensions to describe an EV aggregator business model

- **Aggregation of individual electric vehicles (EVs)** to a virtually combined storage stack.
- **Additional uncertainty** of electric vehicles must be captured:
  - Arrival and departure times, as well as consumption
- **Operational limits** of the virtual battery are affected and change over the simulation time
  - (Dis)charge power and the aggregated battery filling level depend on the number connected EVs
  - Users have preferences on their EV's battery filling level
    - In general
    - Specifically at the departure time
  - EVs might not be part of the virtual battery if, they cannot provide flexibility,
    i.e. they must be charged at full rate to meet a minimum filling level,
    but get part of the virtual battery after having reached the required minimum filling level.

Data (1/2) – Mobility Behavior

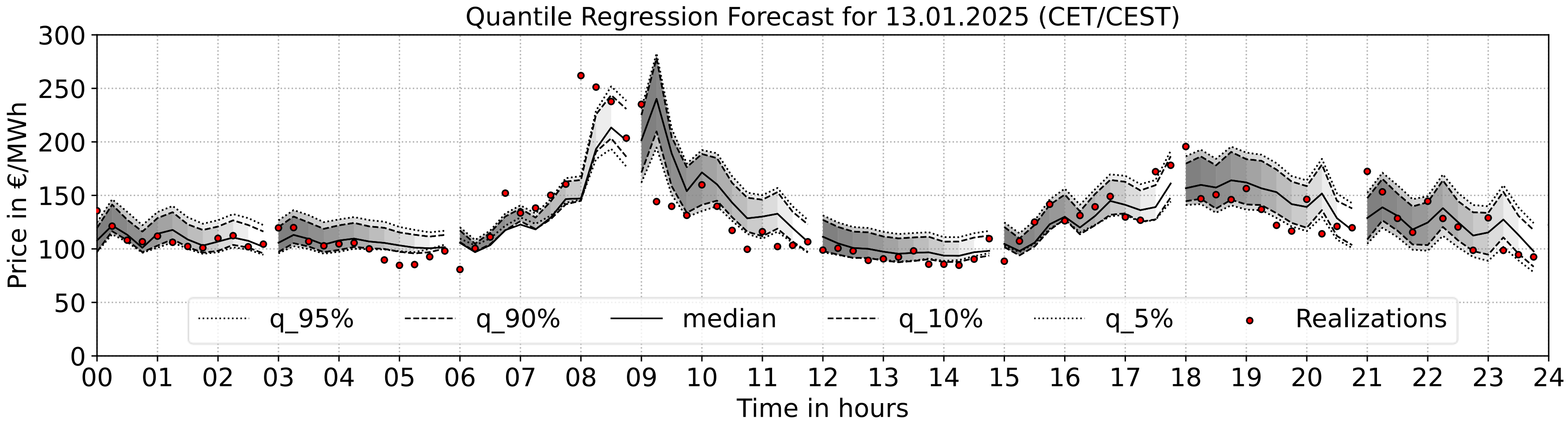
- Driving profile generation
  - Arrival and departure information is taken from Mobilität in Deutschland 2023 (MiD), probability distributions are derived with the emobpy Python library.
  - Four different vehicles are considered: Tesla Model 3, VW ID3, Renault Zoe, Hyundai Kona
  - Distance driven per year approx. 10.000 km (long trips are underreported by MiD 2023).
  - (Dis)charge power per EV: 11 kW, charging only at home
  - The study case considers 200 EVs belonging to the aggregator.

- At arrival, EVs either belong to the *must charge* or *flexible* category.

- The Least Square Monte Carlo Simulation abstracts from individual EV data

Data (2/2) – ID1 Prices

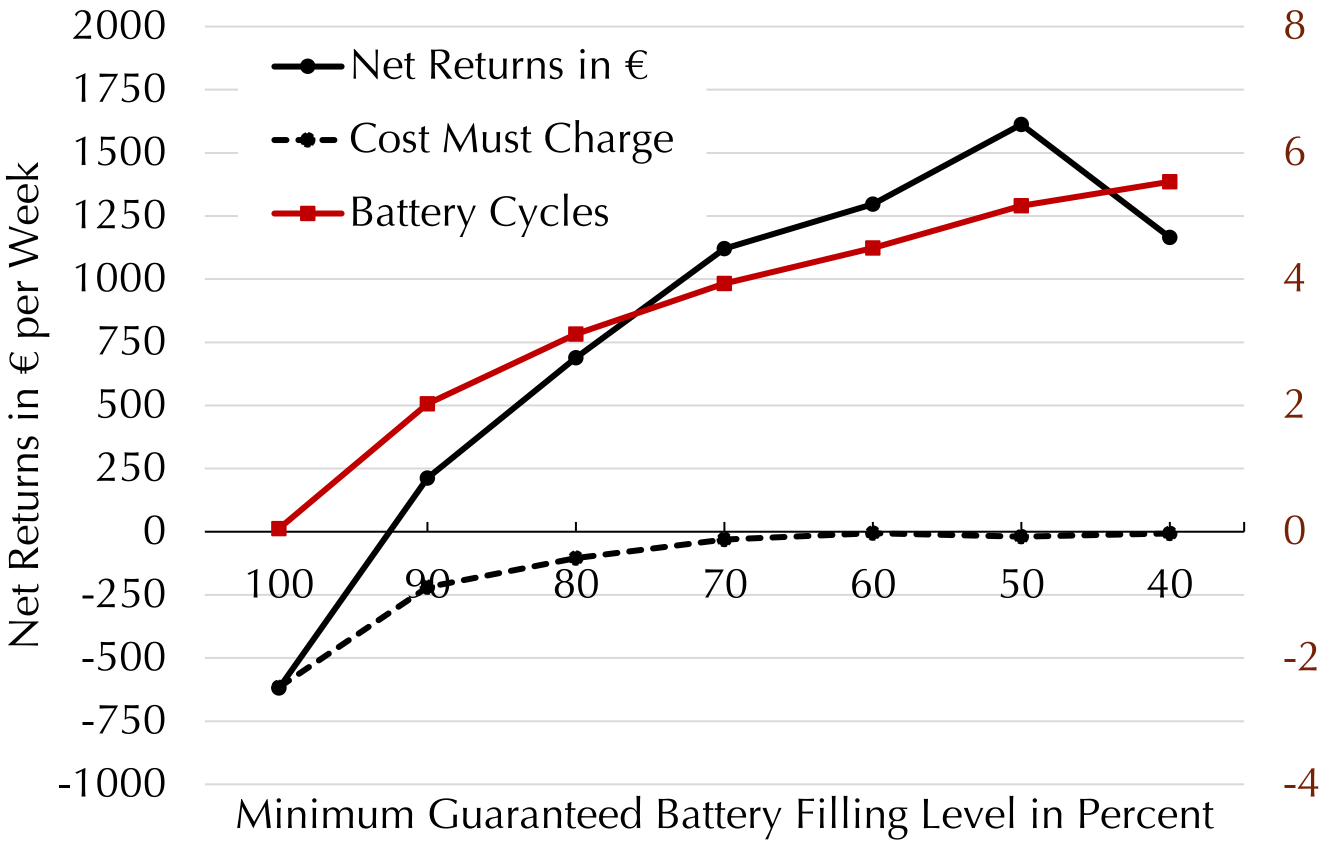
- **ID1 price index** of epexspot: weighted mean price of all cont. trades within the last hour
- Observable ID1 price characteristics: Reaction to RES forecast errors, unforeseen outages
- Multiple Linear Quantile Regression as Forecast Tool
  - $Y_t = \beta_1 L_{1qh}(Y_t) + \beta_2 L_{2qh}(Y_t) + \beta_3 L_{3qh}(Y_t) + \beta_4 L_{4qh}(Y_t) + \beta_5 L_{1d}(Y_t) + \beta_6 L_{2d}(Y_t) + \beta_7 L_{7d}(Y_t) + \beta_8 Renewable + \beta_9 Demand + \beta_{10} Mon + \beta_{11} Sat + \beta_{12} Sun$
  - Historical ID1 price information (lags: 1,2,3,4 quarter hours; 1,2,7 days)
  - EntsoE Day-Ahead forecasts on national renewable generation and load
- Simulation of autoregressive process to get price trajectories.



Impact of Minimum Battery Filling Level (1/2)

Insights from a winter week with a low residual load, but high daily average price spreads (ID1)
→ Week 3, 13. – 19. January 2025

- **Net returns:**
  Decreasing marginal utility
- **Must charge (inflexible) demand:**
  Negligible below 70%
- **Battery cycling**:
  Trend towards one cycle per day



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Impact of Minimum Battery Filling Level (2/2)

Differentiation between minimum filling level during daytime and nighttime (7pm, 7am)

Battery Cycles

Minimum filling level (daytime) / Minimum filling level (nighttime)

	100%	90%	80%	70%	60%	50%	40%
100%							
90%	1.07	2.02					
80%	1.41	2.41	3.13				
70%	1.76	2.78	3.24	3.93			
60%	2.00	2.89	3.42	4.07	4.49		
50%	2.13	3.08	3.71	4.28	4.71	5.16	
40%	2.18	3.17	4.02	4.41	4.95	5.21	5.54

Net returns in €

Minimum filling level (daytime) / Minimum filling level (nighttime)

	100%	90%	80%	70%	60%	50%	40%
100%	-619.07						
90%	-143.40	212.11					
80%	295.84	553.09	688.69				
70%	660.46	976.20	1113.53	1120.83			
60%	812.66	1233.68	999.91	1108.94	1296.42		
50%	889.99	1364.97	1595.05	1399.27	1390.73	1612.60	
40%	996.95	1399.26	1681.76	1801.62	1874.69	1501.95	1165.37

Flex. Charge in €/MWh

Minimum filling level (daytime) / Minimum filling level (nighttime)

	100%	90%	80%	70%	60%	50%	40%
100%							
90%	121.99	133.72					
80%	118.05	131.49	135.24				
70%	116.28	127.82	132.71	135.74			
60%	117.27	127.95	131.87	136.85	137.95		
50%	114.52	126.19	129.73	134.13	137.62	139.63	
40%	115.44	126.07	130.13	132.63	137.71	140.61	143.49

Flex. Discharge in €/MWh

Minimum filling level (daytime) / Minimum filling level (nighttime)

	100%	90%	80%	70%	60%	50%	40%
100%							
90%	152.09	160.97					
80%	153.23	162.79	167.65				
70%	159.10	164.03	167.44	170.05			
60%	161.23	168.31	164.54	167.28	170.88		
50%	160.32	167.83	170.00	167.95	170.43	173.18	
40%	163.78	169.77	169.02	172.70	171.91	171.28	167.61

Conclusion and Outlook

Preliminary Summary

- Already small flexibility during the day strongly increases net returns. Then decaying marginal utility.
- Flexibility only during night implies limited cycling).
- At low min. filling level at night, min. filling level during the day impacts cycling, but only limited impact on returns.

Foreseen extensions

- Assessment of other weeks of the year with different price characteristics
- Comparison to unidirectional smart charging
- Method to determine promising tariff time windows based on historical ID1 prices
- (Dis)charge power reduction in certain hours of the day

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Thank you for your attention!

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