Benchmarking Flexible Electric Loads Scheduling Algorithms under Market Price Uncertainty

Algorithms for optimal trading in day-ahead and reserve markets, and scheduling flexible energy demand

Koos van der Linden Natalia Romero Germán Morales-España
Mathijs de Weerdt

Delft University of Technology, The Netherlands

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Motivation and problem introduction

Challenge: Maintain balance between power supply and demand.

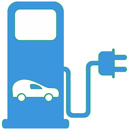
Changes in the power system

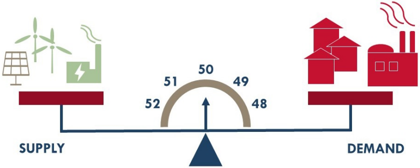
- renewable energy is
  - intermittent
  - uncertain
  - uncontrollable
- new loads such as heat pumps, airconditioning, and electric vehicles are
  - significantly larger than other household demand, and
  - more flexible (and therefore also less predictable)

commons.wikimedia.org/wiki/File:Electric_Car_recharging.jpg

Objective of planning algorithms

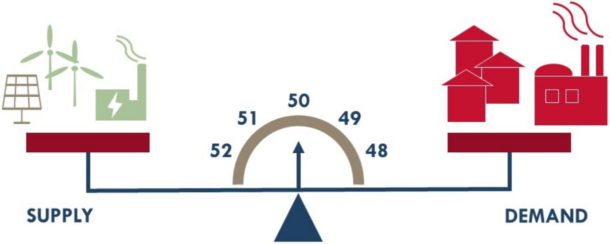
- Schedule **flexibility** efficiently
  (e.g. electric vehicles, greenhouses, traders)
- Reduce operational **costs**
- Help **balancing** the grid



AEMO Energy Live. Managing frequency in the power system.
http://energylive.aemo.com.au/Energy-Explained/Managing-frequency-in-the-power-system

Motivation: Grid imbalance regulation with electric vehicles



Case study: The Netherlands

- Average imbalance per PTU: ~50-150MWh
- EVs required to restore the balance: ~60000 (0.8%)
- Actual number EVs: ~26000 BEVs, ~98000 PHEVs

AEMO Energy Live. Managing frequency in the power system.
http://energylive.aemo.com.au/Energy-Explained/Managing-frequency-in-the-power-system

TenneT (Apr. 2011). Imbalance Management TenneT Analysis report.

Netherlands Enterprise Agency (2018). Statistics Electric Vehicles in the Netherlands.

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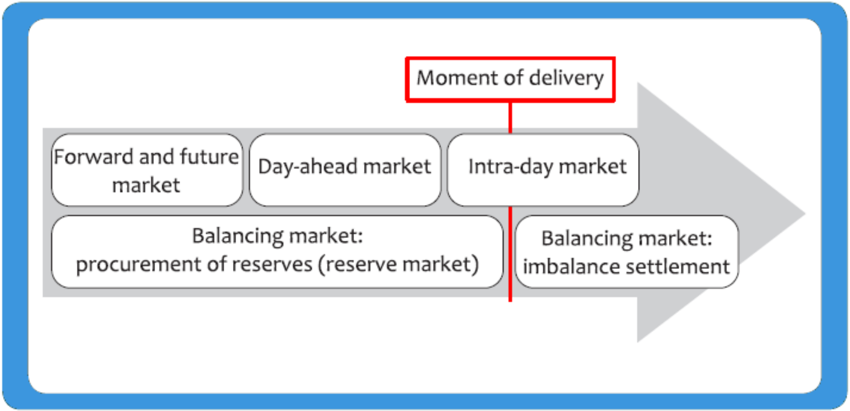
Flexibility is valorized in different energy markets



KU Leuven Energy Institute. The current electricity market design in Europe. https://set.kuleuven.be/ei/images/EI_factsheet8_eng.pdf/

Uncertainty in energy prices and markets

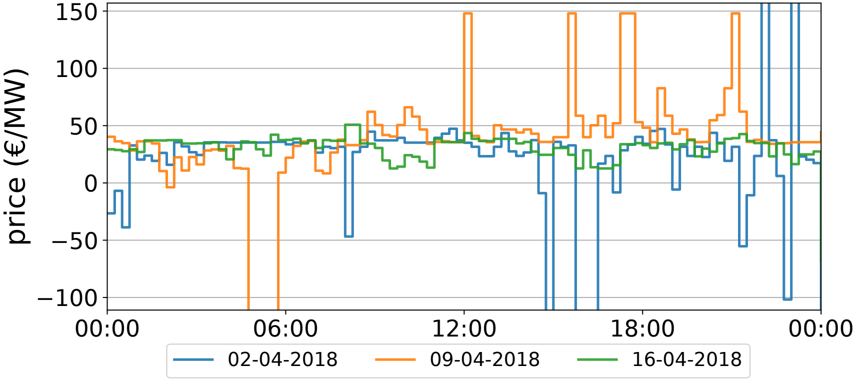
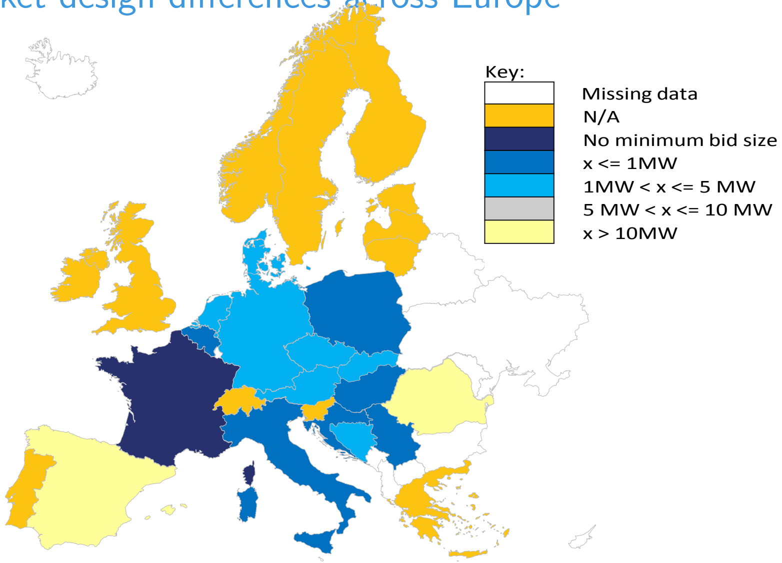


Figure: Imbalance price in the Dutch market

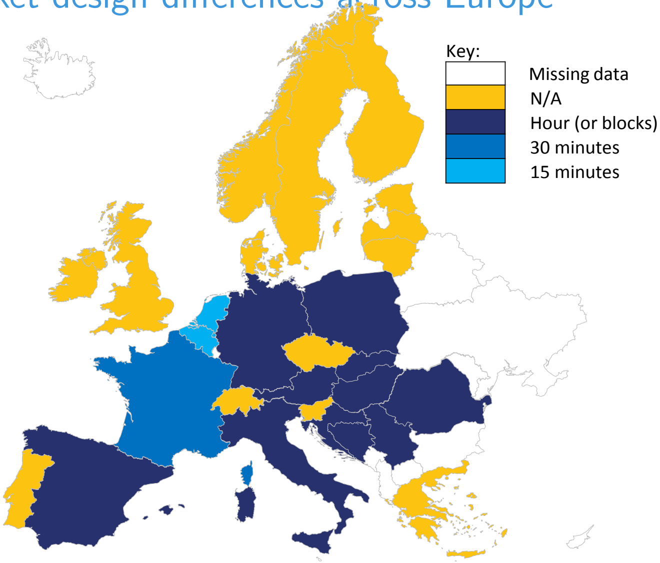
TenneT. Market Information. http://www.tennet.org/bedrijfsvoering/ExporteerData.aspx

Market design differences across Europe



ENTSO-E WGAS. Survey on ancillary services procurement, balancing market design 2017.
https://docstore.entsoe.eu/Documents/Publications/Market%20Committee%20publications/ENTSO-E_AS_survey_2017.pdf

Market design differences across Europe

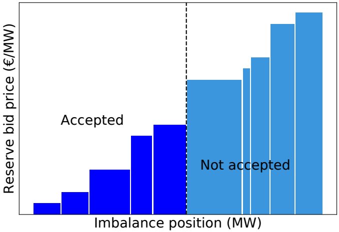


ENTSO-E WGAS. Survey on ancillary services procurement, balancing market design 2017.
https://docstore.entsoe.eu/Documents/Publications/Market%20Committee%20publications/ENTSO-E_AS_survey_2017.pdf

Reserves and uncertainty

Reserves in the Dutch market (TenneT)

- Primary Reserves: Frequency Containment Reserves (FCR)
- Secondary Reserves: Automated Frequency Restoration Reserves (aFRR)
  - Contracted
  - Voluntary
- Tertiary Reserves: Manual Frequency Restoration Reserves (mFRR)



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- Motivation and problem introduction
  - Flexible Electric Loads scheduling
  - Electricity Markets and Uncertainty
- Solutions
  - **Solution methods and algorithms**
- Evaluation
  - Benchmarking
- Conclusion

Solution methods

Trivial solutions and solutions from the literature

- DI Direct charging
- OP Charging based on the optimal expected price
- QO Quantity-only reserve bidding
- DT Deterministic price bidding based on probability of acceptance
- MR MaxReg heuristic

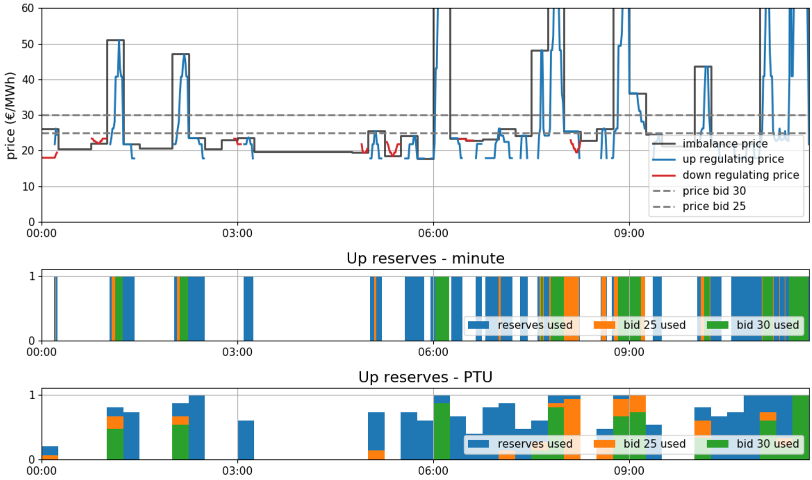
New solutions

- SO1 One stage stochastic optimization
- SO2 Two stage stochastic optimization

E. Sortomme and M. A. El-Sharkawi (2011). "Optimal charging strategies for unidirectional vehicle-to-grid". In: IEEE Transactions on Smart Grid 2.1, pp. 131–138

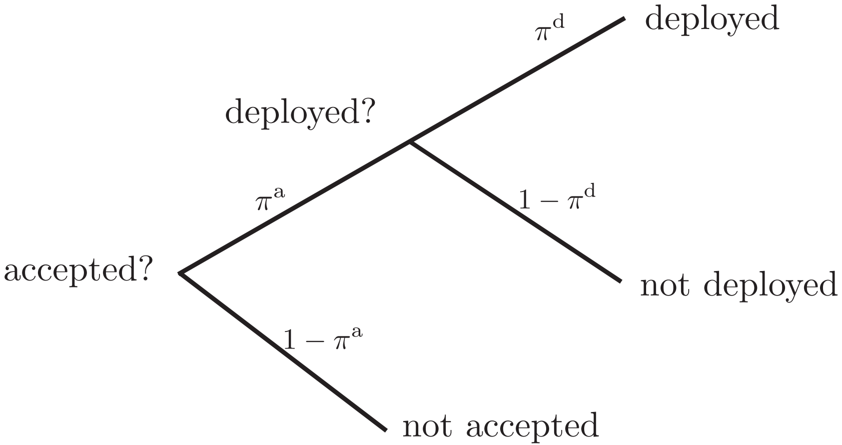
M. R. Sarker, Y. Dvorkin, and M. A. Ortega-Vazquez (Sept. 2016). "Optimal Participation of an Electric Vehicle Aggregator in Day-Ahead Energy and Reserve Markets". In: IEEE Transactions on Power Systems 31.5, pp. 3506–3515

QO - Quantity-only reserve bidding



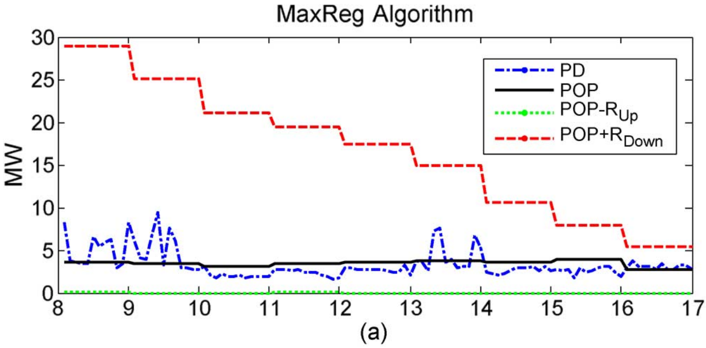
TenneT. Market Information. http://www.tennet.org/bedrijfsvoering/ExporteerData.aspx

DT - Bidding based on probability of acceptance



M. R. Sarker, Y. Dvorkin, and M. A. Ortega-Vazquez (Sept. 2016). "Optimal Participation of an Electric Vehicle Aggregator in Day-Ahead Energy and Reserve Markets". In: IEEE Transactions on Power Systems 31.5, pp. 3506–3515

MR - MaxReg heuristic



- The heuristic determines a preferred operating point (POP)
- When charging more/less is available, reserves are committed
- The MaxReg heuristic chooses a POP that maximizes reserves utilization

E. Sortomme and M. A. El-Sharkawi (2011). "Optimal charging strategies for unidirectional vehicle-to-grid". In:

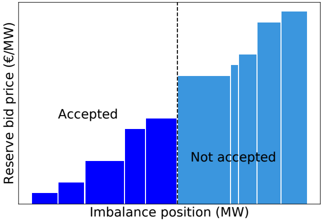
SO1&2- Stochastic optimization

SO1 - One stage stochastic optimization

- Similarly as DT, based on probability of acceptance, but with optimizing expected value over multiple scenario's

SO2 - Two stage stochastic optimization

- Probability of acceptance modelled directly
- Binary variables model whether a reserve bid is accepted or not



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  - **Benchmarking**
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Benchmarking

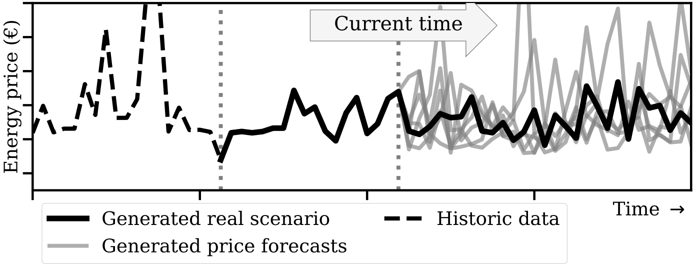
Objectives

- Quantitative analysis
- Online analysis
- Performance under uncertainty and multiple scenario's

Benchmarking Electric Flexible Load Scheduling Algorithms

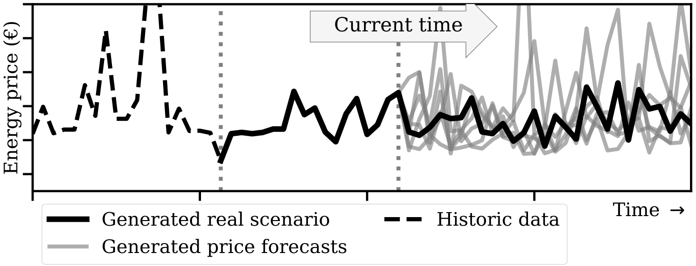
- **Compare** solution methods
  e.g. Probabilistic, Deterministic, Stochastic
- **Change** market configuration
  e.g. Capacity payments, Minimum reserve bid size
- **Online** comparison under **Uncertainty**
  by means of a scenario generator (e.g. ARIMA)

Scenario generation and online evaluation



- Train an ARIMA model M based on historic data
- Use M to generate a 'real' scenario s
- For every time step t in the online simulation:
  - Use M to generate n scenario's S from s starting at t
  - Let the algorithm update its decisions based on S at point t
- Evaluate the algorithm based on the 'real' scenario s

Scenario generation and online evaluation



- Train an ARIMA model M based on historic data
- Use M to generate a 'real' scenario s
- For every time step t in the online simulation:
  - Use M to generate qn scenario's S from s starting at t
  - Choose the n scenario's from S most similar to s
  - Let the algorithm update its decisions based on S at point t
- Evaluate the algorithm based on the 'real' scenario s

Test setup

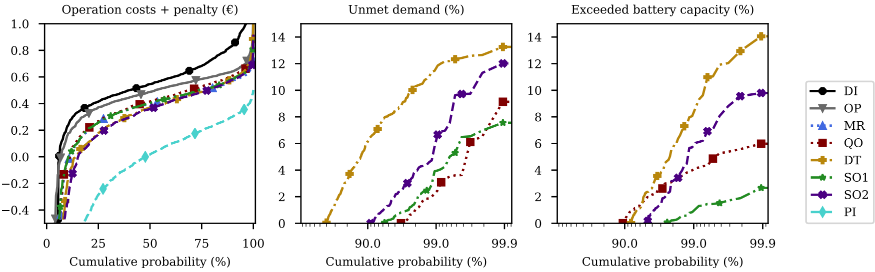
Test objectives

- Measure operation costs
- Measure risk (unmet demand and exceeding the battery capacity)

Test parameters

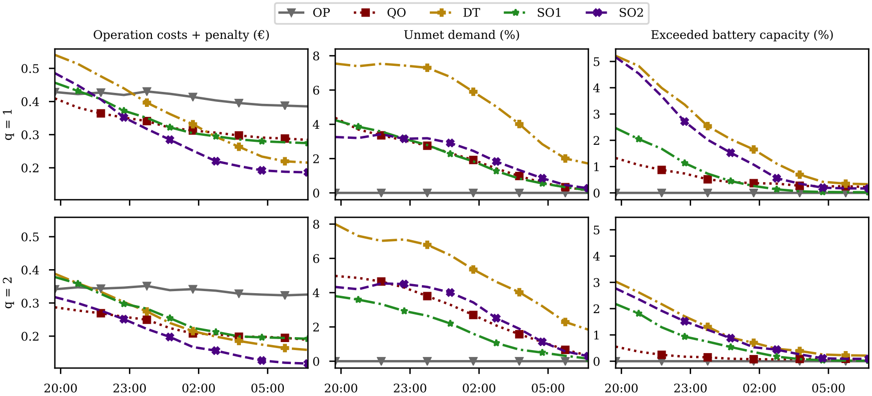
- Dutch market setup (95 historic scenario's from 2016 used to generate 950 test scenario's)
- One EV with a battery capacity of 30kWh, initial SOC of 1kWh, required SOC of 27kWh, a charging speed of 7kW and a charging efficiency of 90%
- DT's desired acceptance probability is set to 50%, SO1's to 80%
- SO1 and SO2 optimize based on 20 scenario's

Benchmarking results - solution distribution



- PI shows the perfect information solution
- Differences are small but statistically significant (as small as 2% of the standard deviation)
- High variance shows importance of dealing with uncertainty
- Distance to PI shows difficulty to find optimal solutions

Benchmarking results - online reacting to uncertainty



- The best 25 scenarios are chosen from the 25q generated scenario's
- Solution quality increases when updating decisions over time
- Data quality influences the algorithm's (relative) performance)

Results table

Results for the Dutch case study. The values shown are the mean ± the standard deviation of the results.

	Costs + penalty (€)		Unmet demand (%)	Exceeded capacity (%)	Run time (s)
q	1	2	1	1	1
DI	0.47±0.51		0.0	0.0	1e–3±2e–3
OP	0.39±0.44		0.0	0.0	1e–3±1e–3
MR	0.27±0.46		0.0	0.0	1e-3±6e-3
QO	0.28±0.50	0.19 (-0.09)	0.08±0.68	0.22±0.80	0.59±0.10
DT	0.21±0.54	0.16 (-0.06)	1.63±2.84	0.33±1.51	0.58±0.08
SO1	0.27±0.48	0.19 (-0.08)	0.11±0.69	0.02±0.21	0.66±0.10
SO2	0.19±0.58	0.12 (-0.07)	0.24±1.14	0.17±1.03	73.8±41.2
PI	-0.25±0.78		0.0	0.0	

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Conclusion

Conclusions

- A simple expected value based analysis does not suffice
- Online decision making is important to deal with uncertainty
- The algorithm's performance is measured with regards to the quality of the provided data
- Stochastic programming helps in finding good solutions that balance operation costs and risk

More info

- Koos van der Linden and Natalia Romero and Mathijs M. de Weerdt (2020). Benchmarking Flexible Electric Loads Scheduling Algorithms under Market Price Uncertainty, arXiv 2002.01246.
- https://github.com/AlgTUDelft/B-FELSA/

Acknowledgements

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