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*

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

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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

Key:
- Missing data
- N/A
- No minimum bid size
- \( x \leq 1 \text{MW} \)
- \( 1 \text{MW} < x \leq 5 \text{MW} \)
- \( 5 \text{MW} < x \leq 10 \text{MW} \)
- \( x > 10 \text{MW} \)

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

Key:

- Missing data
- N/A
- Hour (or blocks)
- 30 minutes
- 15 minutes

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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## Solution methods

### Trivial solutions and solutions from the literature

| Code | Description |
|------|-------------|
| 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

| Code | Description |
|------|-------------|
| SO1  | One stage stochastic optimization |
| SO2  | Two stage stochastic optimization |

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E. Sortomme and M. A. El-Sharkawi (2011). “Optimal charging strategies for unidirectional vehicle-to-grid”. *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”. *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
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

### 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
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            |
| 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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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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