Mid-to long-term modeling of electricity market prices

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|-----------|------------------|-------------------|-------|--|
| 2011 2012 | 110/110/20/20/20 | • | | |
| CITATION | S | | READS | |
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| 1 auth | or: | | | |
| | Martin Klein | | | |
| 9 | German Aeros | pace Center (DLR) | | |
| | 23 PUBLICATIONS | 40 CITATIONS | | |
| | SEE PROFILE | | | |

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Martin Klein

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Gesellschaft für Energiewissenschaft und Energiepolitik e.V. 25. Workshop des Student Chapters

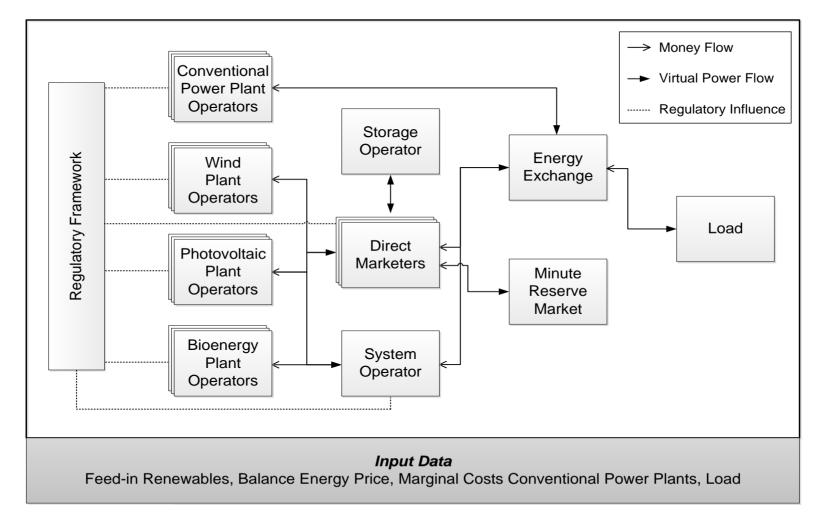
EWI, Köln, 04th May 2018







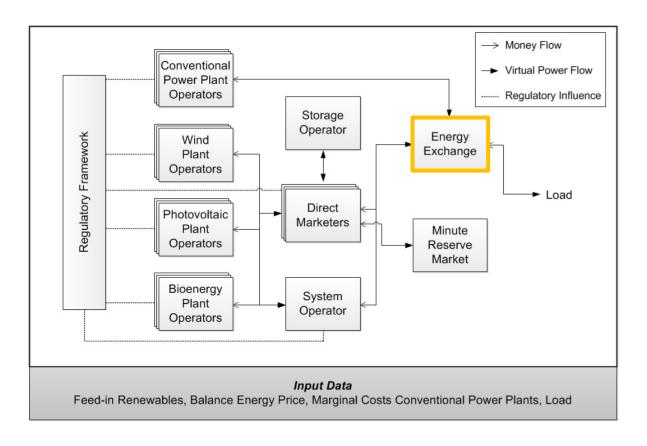
AMIRIS – An Agent-Based Model of the German Electricity System

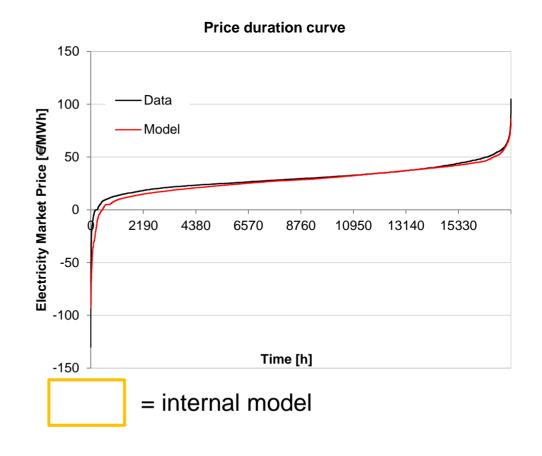




Agent-based model as a container framework

Example of model within model // explicit internal model coupling

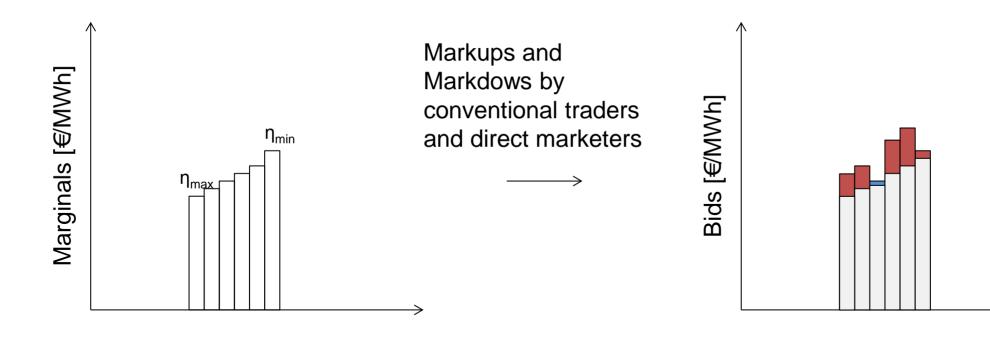






Electricity spot market price modeling

Hybrid fundamental and econometric approach





Electricity spot market price modeling Input and output

Time series:

- **demand** curve (hourly)
- generation potentials for PV and wind (hourly)
- fuel prices for coal, gas and oil (daily)
- power plant unavailabilities (planned) (monthly)
- capacities for all power plant classes (nuclear, lignite, hard coal, gas combined cycle, gas turbine, oil, PV, wind onshore, wind offshore, hydro, biomass, import DRE, storage) (yearly)
- power plant efficiencies (min and max) (yearly)

Constants:

- power plant unavailabilities (unplanned)
- Average block sizes of power plants
- minimum and maximum markups/markdowns on top of the marginal bid of each block

Output: Hourly electricity market prices in €MWh



Data

Sources:

Power Plant Capacities and Efficiencies: Open Power System Data

Demand, Spot Prices: SMARD, BMWi

Planned Unavailabilities: EEX Transparency

Fuel Prices: Quandl / Destatis

We investigate the wholesale electricity market price curve of Germany for the years 2012-2016

• **Training:** Genetic algorithm works on first half of data set (2012 – 2014)

• Validation: on an *independent* data set which was not used for fitting (2015 – 2016)



Genetic algorithm to determine markups

• One gene = one set of possible markups

• Example:
$$\begin{pmatrix} min & max \\ -200 & -10 \\ -30 & 10 \\ -50 & 30 \end{pmatrix}$$
 Nuclear Gas CC

- Pseudo-Code:
 - Evaluate Fitness Of Genepool
 - Remove Low Fitness Solutions
 - Calculate Selection Probabilities
 - For generationSize :
 - Make new Children



Genetic algorithm to determine markups

Multi-objective fitness criteria

| Optimization Criteria | Unit | target t_i | weight w_i |
|--------------------------------------|-------|--------------|--------------|
| Pearson Correlation | 1 | 1.0 | 3 |
| Mean Average Error | €/MWh | 0.00 | 5 |
| Standard Deviation | €/MWh | 16.63 | 3 |
| Mean | €/MWh | 37.74 | 3 |
| Minimum | €/MWh | -221.99 | 1 |
| Maximum | €/MWh | 210.00 | 1 |
| Number of hours with negative prices | 1 | 178 | 2 |



Genetic algorithm to determine markups

• One gene = one set of possible markups

• Example:
$$\begin{pmatrix} -200 & -10 \\ -30 & 10 \\ -50 & 30 \end{pmatrix}$$

- Pseudo-Code:
 - Evaluate Fitness Of Genepool
 - Remove Low Fitness Solutions
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 - For generationSize s:
 - Make new Children

• Multi-objective Fitness Evalution:

| Optimization Criteria | Unit | target t_i | weight w_i |
|--------------------------------------|-------|--------------|--------------|
| Pearson Correlation | 1 | 1.0 | 3 |
| Mean Average Error | €/MWh | 0.00 | 5 |
| Standard Deviation | €/MWh | 16.63 | 3 |
| Mean | €/MWh | 37.74 | 3 |
| Minimum | €/MWh | -221.99 | 1 |
| Maximum | €/MWh | 210.00 | 1 |
| Number of hours with negative prices | 1 | 178 | 2 |

• Make new children with random crossover

$$\begin{pmatrix}
-200 & -10 \\
-30 & 10 \\
-50 & 30
\end{pmatrix} + \begin{pmatrix}
-300 & -30 \\
-70 & 30 \\
-20 & 60
\end{pmatrix} \rightarrow \begin{pmatrix}
-200 & -10 \\
-30 & 10 \\
-20 & 60
\end{pmatrix}$$



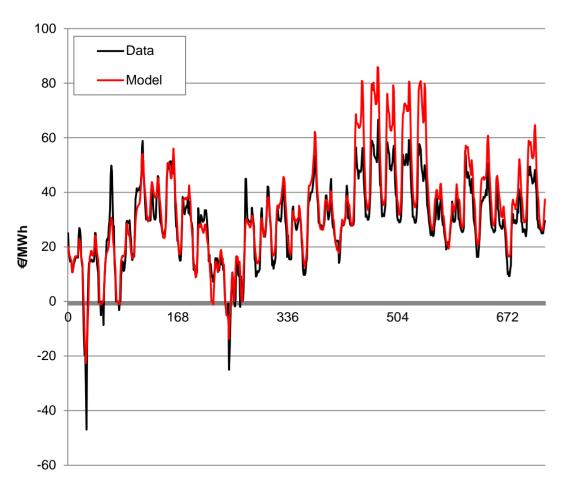
Validation - Descriptive statistics

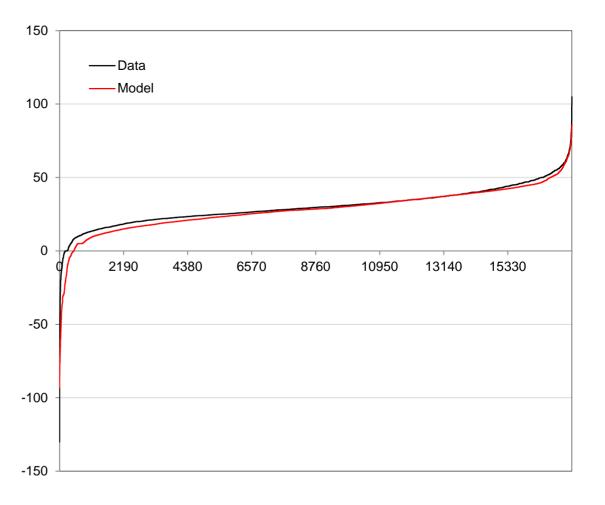
| DESCRIPTIVE STATISTICS Model vs. Data (2015 – 2016) | |
|---|------|
| Pearson Correlation | 0.87 |
| Rank Correlation | 0.89 |
| MAE [€MWh] | 4.79 |
| RMSE [€MWh] | 6.78 |

| SHAPE PARAMETERS | DATA | MODEL |
|------------------|---------|--------|
| Mean [€MWh] | 30.30 | 28.73 |
| Std.D. [€MWh] | 12.64 | 13.10 |
| # Hours < 0€MWh | 223 | 446 |
| Min [€MWh] | -130.09 | -57.93 |
| Max [€MWh] | 104.96 | 85.90 |



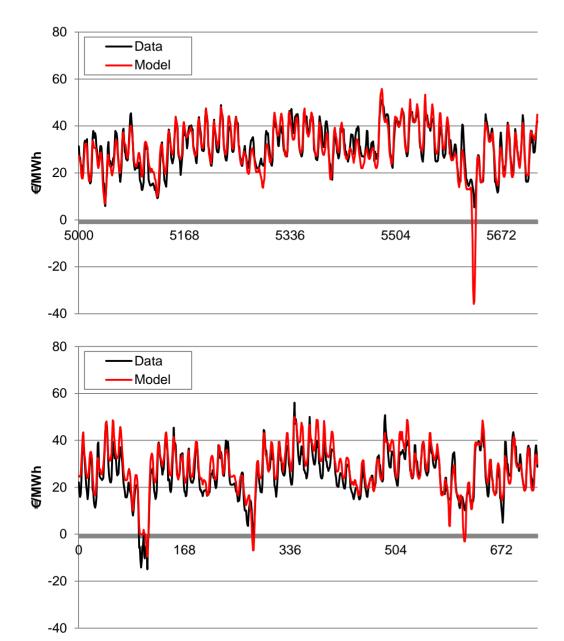
Electricity spot market price modelingResults

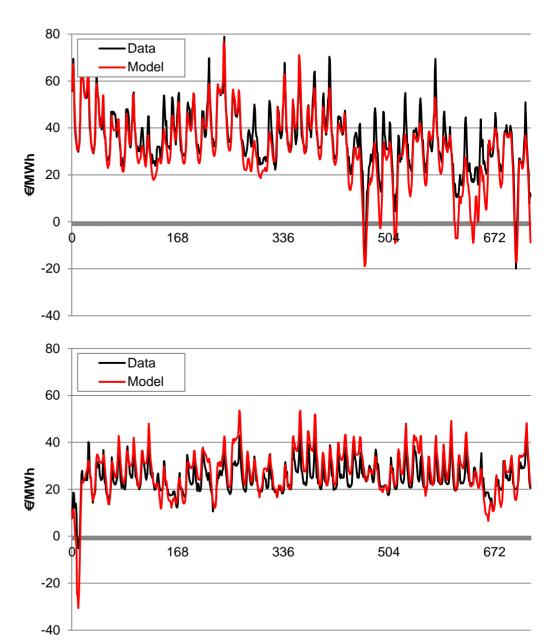






Further randomized examples

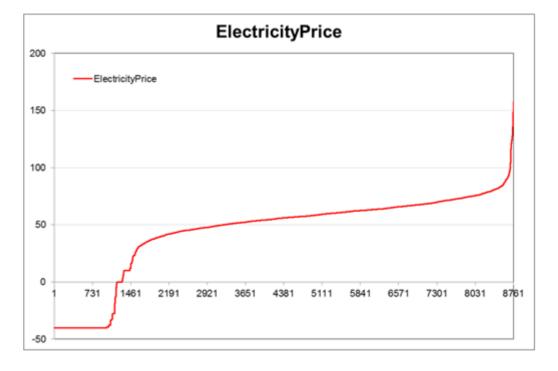




Discussion and outlook

- Novel hybrid method to model electricity market prices is presented
- Combines fundamental bidding mechanism with a machine learning algorithm
- Very good agreement with validation data set (high correlation, low mean average error)
- Capable of reproducing the stylized facts of spot market prices including negative prices, high volatility and kurtosis
- Open Question: To what extent are the markup values characteristic for the technology class and to what extent to the "whole" power plant park?
- Can this approach be used for long-term energy scenarios?

Example Scenario 2035: VRE 50%, RES 60%; less coal, security of supply ensured with gas power plants and some dispatchable imports, demand increase 1%/a, fossil fuel prices on same level as of today,





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Contact





