The impact of renewable energy forecasts on intra-day electricity prices

Sergei Kulakov & Florian Ziel

University of Duisburg-Essen

June 1, 2018
Strommarkttreffen

Announcement: INREC 2018

Call-for-Papers for the 7th International Ruhr Energy Conference (INREC)

Uncertainties in Energy Markets

September 24-25, 2018, Essen, Germany

- ▶ Keynotspeakers:
  - Prof. Stein-Erik Fleten, NTNU Trondheim (NOR)
  - Prof. Andreas Löschel, University of Münster (GER)
  - Prof. Rafał Weron, Wrocław UST(POL)
- ▶ Best paper award (sponsored by GEE)
- ▶ Organizers: Prof. Christoph Weber, Prof. Florian Ziel
- ▶ Abstract submission deadline: June 24, 2018

Basic motivation

▶ market structure of the German EPEX SPOT SE
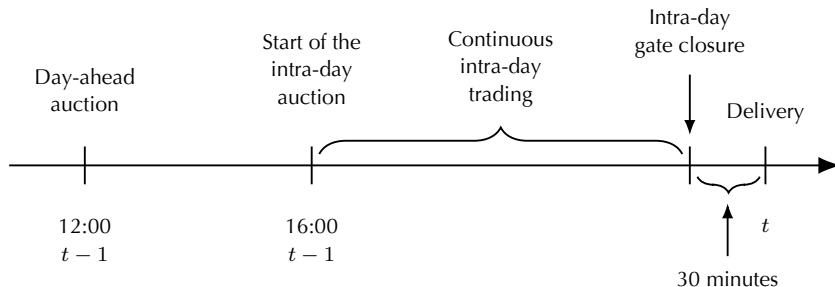
▶ The intra-day market
  – is temporally closer to the moment of electricity delivery
  – is supplied with more accurate forecasts as to the wind and solar supply
▶ Part of the difference between day-ahead and intra-day prices stems from errors in wind and solar power forecasts, [Kallabis et al., 2016]
▶ For empirics we consider hourly ID1 (volume weighted intra-day price)
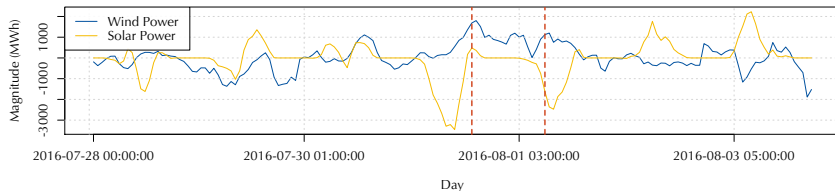
Basic motivation: evidence from EPEX SPOT SE
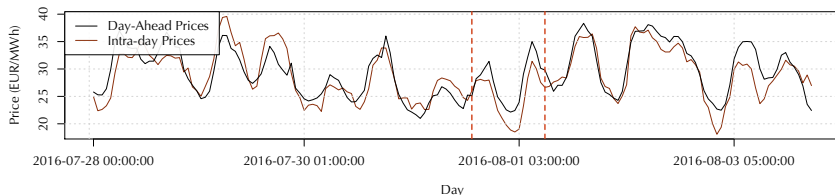
Figure: Dynamics of day-ahead and intra-day prices (upper graph) vs. differences between actual and day-ahead forecast values of wind and solar supply (lower graph) for a one-week sample from July, 27 to August, 03, 2016.

Three benchmark models for the intra-day prices

▶ Naive

$$P_t^{naive} = P_t^{DA} + \varepsilon_t \tag{1}$$

- ▶ where
  - P^{DA} day-ahead price
  - ε_t error term

▶ Linear 1

$$P_t^{lm_1} - P_t^{DA} = \beta_0 + \beta_1 \max(W_t^{\Delta}, 0) + \beta_2 \min(W_t^{\Delta}, 0) + \beta_3 \max(S_t^{\Delta}, 0)$$
$$+ \beta_4 \min(S_t^{\Delta}, 0) + \beta_5 W_t^{A} + \beta_6 S_t^{A} + \varepsilon_t \tag{2}$$

- ▶ where
  - W_t^{Δ} wind power forecast
  - S_t^{Δ} solar power forecast
  - W_t^{A} wind energy volume
  - S_t^{A} solar energy volume
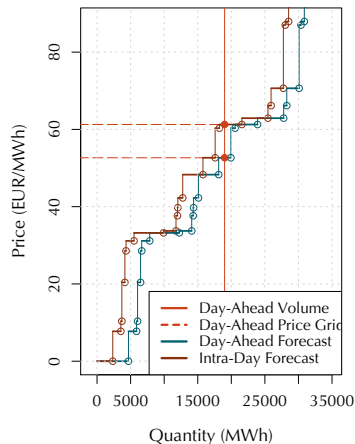
▶ Linear 2

$$P_t^{lm_2} = \beta_0 + \beta_7 P_t^{DA} + \beta_1 \max(W_t^{\Delta}, 0) + \beta_2 \min(W_t^{\Delta}, 0) + \beta_3 \max(S_t^{\Delta}, 0)$$
$$+ \beta_4 \min(S_t^{\Delta}, 0) + \beta_5 W_t^{A} + \beta_6 S_t^{A} + \varepsilon_t \tag{3}$$

▶ models similarly to [Kiesel and Paraschiv, 2017], [Ziel, 2017]

Price effect can be explained by supply stack/ merit order

▶ Overestimated RES supply might lead to different price reductions
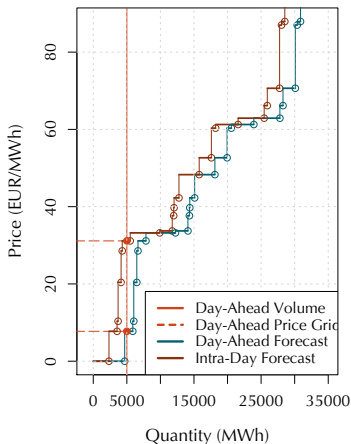
Auction curves in day-ahead wholesale market:
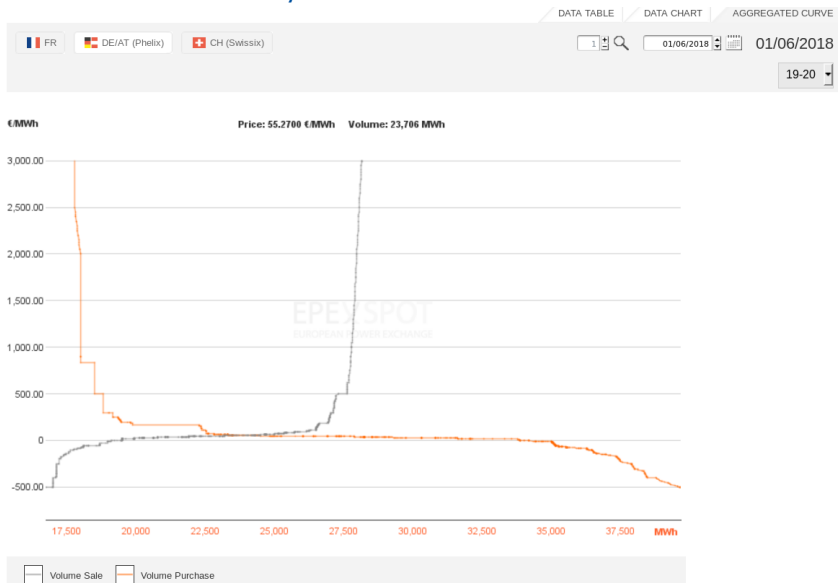
source: http:www.epexspot.comenmarket-datadayaheadauctioncurveauction-aggregated-curve2018-06-01DE193

Modeling and forecasting of day-ahead auction curves
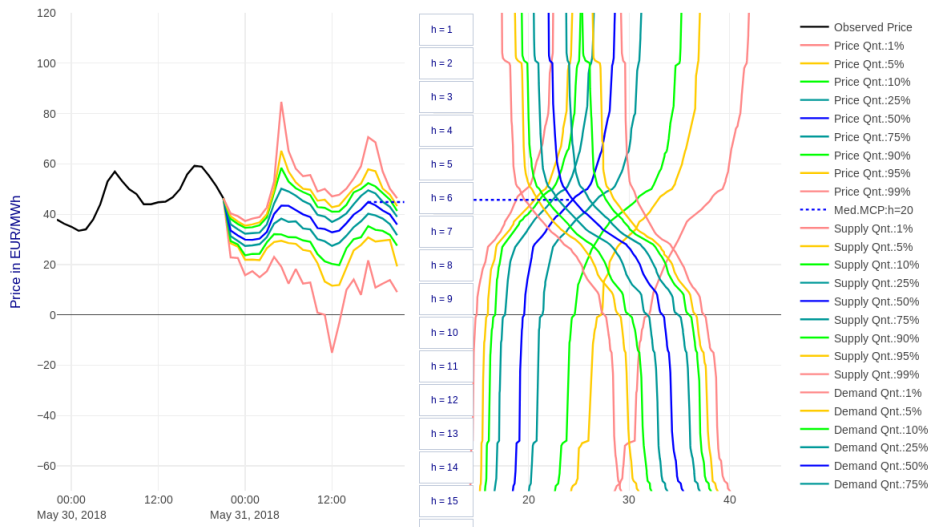
▶ for online tool based on [Ziel and Steinert, 2016] see
uee.wiwi.uni-due.de

Two perspectives on the market, e.g. [Knaut and Paulus, 2016]
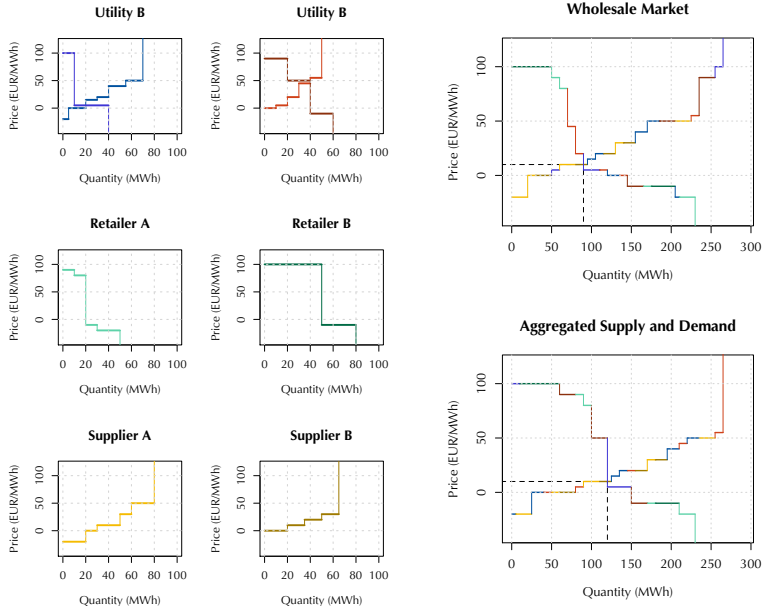
Elastic demand curve vs. its inelastic analogue
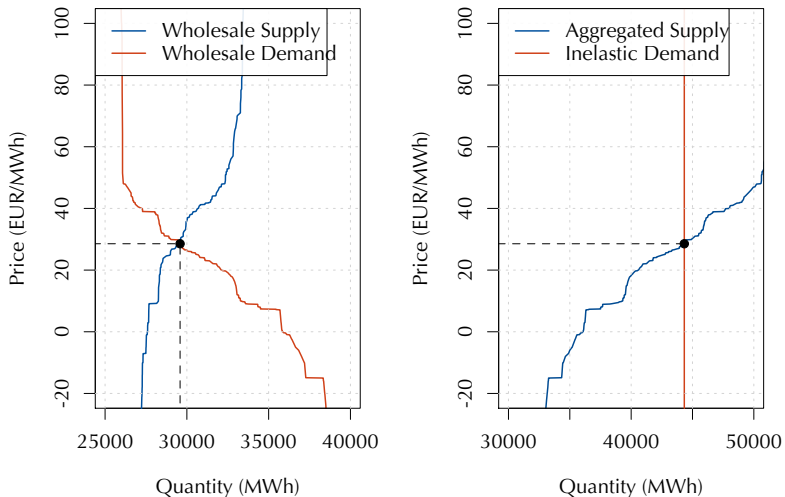
Figure: A wholesale market equilibrium on 2017-04-02 08-00-00 CET (left plot) vs. its manipulated form with an inelastic demand curve (right plot)

Transformation of supply and demand curves

▶ Formulas for transforming the curves are given in [Coulon et al., 2014]
  – the expression for an inelastic demand curve reads

$$Dem_t^{inelastic} = WSDem_t^{-1}(P_{\max}) \qquad (4)$$

  ▶ where
    • a demand curve in a wholesale market is denoted by $WSDem$
    • $P_{\max} = 3000$ as prescribed by the regulation of EPEX
  – equation for an inverse supply curve can be written as

$$Sup_t^{-1}(z) = WSSup_t^{-1}(z) + WSDem_t^{-1}(P_{\min}) - WSDem_t^{-1}(z) \qquad (5)$$

  ▶ where
    • a supply curve in a wholesale market is denoted by $WSSup$
    • $P_{\min} = -500$

Our first model of intra-day prices

▶ Model nlm_1 has the following specification

– the expression for a shifted supply curve reads

$$Sup_t^{nlm_1}(z,\boldsymbol{\beta}_{nlm_1}) = Sup_t\Big(z - \beta_8 - \beta_9\max(W_t^{\Delta},0) - \beta_{10}\min(W_t^{\Delta},0) \qquad (6)$$
$$-\beta_{11}\max(S_t^{\Delta},0) - \beta_{12}\min(S_t^{\Delta},0) - \beta_{13}W_t^{A} - \beta_{14}S_t^{A}\Big)$$

▶ where
- $\boldsymbol{\beta}_{nlm_1} = (\beta_8,...,\beta_{14})$
- W_t^{Δ}, S_t^{Δ} wind and solar forecasting error
- W_t^{A}, S_t^{A} wind and solar energy

– the intra-day price model can be represented as follows

$$P_t^{nlm_1}(\boldsymbol{\beta}_{nlm_1}) = Sup_t^{nlm_1}(Dem_t^{inelastic},\boldsymbol{\beta}_{nlm_1}) + \varepsilon_t \qquad (7)$$

– vector of coefficients $\boldsymbol{\beta}$ is estimated by solving the following non-linear least squares problem

$$\widehat{\boldsymbol{\beta}}_{nlm_1} = \underset{\boldsymbol{\beta}\in\mathbb{R}^7}{\arg\min}\left(P_t^{ID} - P_t^{nlm_1}(\beta_8,...,\beta_{14})\right)^2 \qquad (8)$$

▶ R function `optim` was used as a major optimization tool

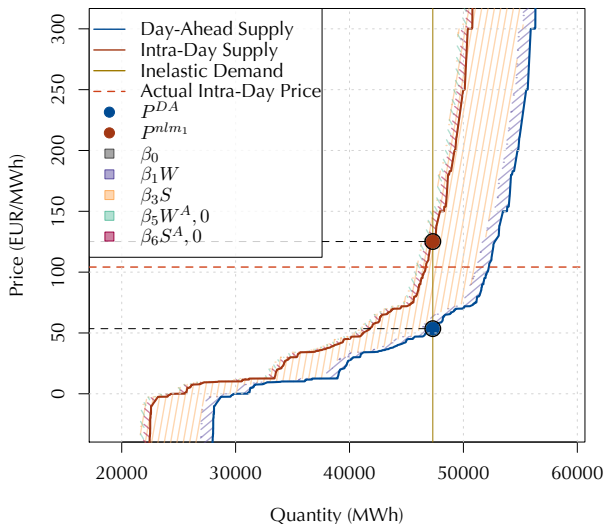# An example of the functioning of the model nlm_1

Figure: The figure shows how the shift of the supply curve allows us to obtain price P^{nlm_1}.

Our second model of intra-day prices

▶ The model nlm_2 aims to incorporate both linear and non-linear effects
  – the price equation of the model can thus be written as follows

$$P_t^{nlm_2}(\boldsymbol{\beta}_{nlm_2}) = \underbrace{P_t^{lm_2}(\beta_0, ..., \beta_7)}_{\text{linear component}} + \beta_{15} \underbrace{P_t^{nlm_1}(\beta_8, ..., \beta_{14})}_{\text{non-linear component}} + \varepsilon_t \qquad (9)$$

  ▶ note that
    • the price produced by linear model lm_2 is given by

$$P_t^{lm_2}(\beta_0, ..., \beta_7) = \beta_0 + \beta_7 P_t^{DA} + \beta_1 \max(W_t^{\Delta}, 0) + \beta_2 \min(W_t^{\Delta}, 0)$$
$$+ \beta_3 \max(S_t^{\Delta}, 0) + \beta_4 \min(S_t^{\Delta}, 0) + \beta_5 W_t^A + \beta_6 S_t^A \quad (10)$$

    • the price produced by non-linear model nlm_1 can be written as

$$P_t^{nlm_1}(\beta_8, ..., \beta_{14}) = Sup_t^{nlm_1}(Dem_t^{inelastic}, \boldsymbol{\beta}_{nlm_1}) \qquad (11)$$

    ▶ it follows that model nlm_2 depends on vector $\boldsymbol{\beta}_{nlm_2} = (\beta_0, ..., \beta_{15})$
  – writing the respective non-linear least squares problem yields

$$\widehat{\boldsymbol{\beta}}_{nlm_2} = \underset{\beta \in \mathbb{R}^m}{\arg \min} \left(P_t^{ID} - P_t^{nlm_2}(\beta_0, ..., \beta_{15}) \right)^2 \qquad (12)$$

Model comparison

▶ The obtained β-coefficients for the year 2016 are summarized in the table below

	Multiplier	lm_1	lm_2	nlm_1	nlm_2
β_0	–	-0.19777	1.24052	–	0.10064
β_1	$\max(W_t^{\Delta}, 0)$	-0.00039	-0.00040	–	0.00000
β_2	$\min(W_t^{\Delta}, 0)$	-0.00214	-0.00209	–	-0.00002
β_3	$\max(S_t^{\Delta}, 0)$	-0.00043	-0.00015	–	0.00000
β_4	$\min(S_t^{\Delta}, 0)$	-0.00258	-0.00273	–	-0.00002
β_5	W_t^{A}	0.00009	0.00005	–	-0.00000
β_6	S_t^{A}	0.00000	-0.00002	–	-0.00000
β_7	P_t^{DA}	–	0.97019	–	0.39731
β_8	–	–	–	0.00004	-0.00061
β_9	$\max(W_t^{\Delta}, 0)$	–	–	0.33663	0.90624
β_{10}	$\min(W_t^{\Delta}, 0)$	–	–	0.39478	0.24175
β_{11}	$\max(S_t^{\Delta}, 0)$	–	–	0.86325	1.48092
β_{12}	$\min(S_t^{\Delta}, 0)$	–	–	0.37144	0.25544
β_{13}	W_t^{A}	–	–	-0.02659	-0.06149
β_{14}	S_t^{A}	–	–	-0.02590	-0.01337
β_{15}	$P_t^{nlm_1}$	–	–	–	0.55152

Model comparison

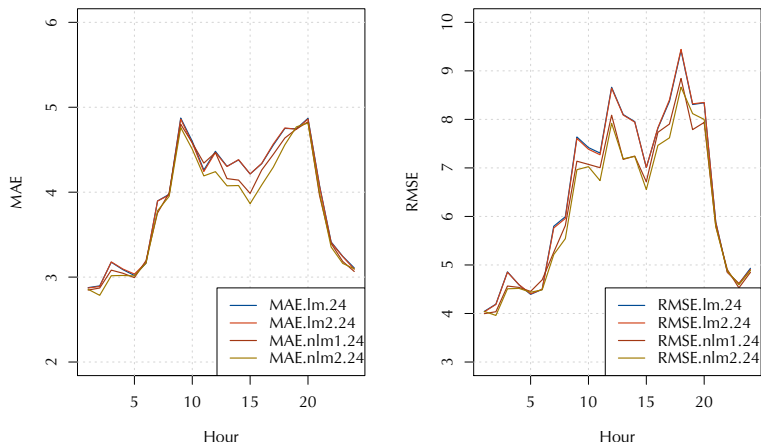▶ The models yield the following MAE and RMSE values for each of the 24 hours in a day

Figure: MAE and RMSE values produced by the models

Model comparison

▶ The out-of-sample performance of the models can be described as follows

	MAE	RMSE
Naive	4.827	7.869
lm_1	4.264	7.230
lm_2	4.267	7.261
nlm_1	4.331	7.233
nlm_2	**4.235**	**7.085**

  – both MAE and RMSE tests were conducted using a rolling time window
    ▶ the number of in-sample observations equals to 365 days
      • year 2016 was taken as an initial time frame
    ▶ the out-of-sample horizon is limited to 365 days too
    ▶ the window size is 24 hours

▶ The obtained results can be summarized as follows
  – linear model lm_2 fails to surpass the model lm_1
  – model lm_1 produces lesser MAE and RMSE errors than the model nlm_1
  – model nlm_2 bears the smallest MAE and RMSE values

Model comparison

▶ Following the DM-test, the model nlm_2 is better than the model lm_1, though not significantly
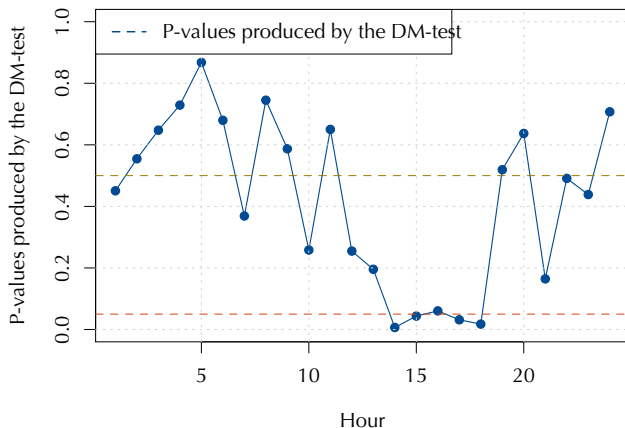

Figure: Results of the DM-test for each hour of the day for the year 2017

Concluding remarks

▶ By taking advantage of the empirical supply and demand curves we showed that

   – equilibrium in a wholesale market coincides with an intersection between aggregated supply and demand curves

   – it is possible to model intra-day prices given the day-ahead data and forecasting errors in wind and solar power

   – a model which includes both linear and non-linear effects tends to outperform a simple linear model

▶ Steps to be undertaken

   – consider opening auction

   – include demand/load forecasts,

   – incorporate unavailability of power plants (outages), curtailment

   – a more elaborated optimization tool can be employed

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