An Electricity Price Modeling Framework for Renewable-Dominant Markets

M. Hain T. Kargus H. Schermeyer

M. Uhrig-Homburg W. Fichtner

Karlsruhe Institute of Technology (KIT)

International Ruhr Energy Conference, September 2022

This presentation is based on a revised and extended version of the earlier paper *Hain, Martin; Schermeyer, Hans; Uhrig-Homburg, Marliese; Fichtner, Wolf (2017): An Electricity Price Modeling Framework for Renewable- Dominant Markets. Karlsruhe (Working Paper Series in Production and Energy, 23).*

Renewable-Dominant Markets

- Growing share of renewables in electricity markets reinforces weather-induced patterns and risks
- Fundamental market changes are challenging for established models in risk management applications
- Using long time series of weather data instead of limited price data series
- Modeling concrete scenarios of temporal as well as spatial distributions of renewable capacity

$\rightarrow$ Hybrid modeling framework connecting a weather model with a structural electricity price model

Why another model?

- State-of-the-art modeling approaches for electricity prices can broadly be separated in the categories:
  - Structural
    - Detailed modeling of price processes
    - Assumed fundamental relationship of input
    - Selected representatives: Bessembinder and Lemmon (2002), Eydeland and Wolyniec (2003), Wagner (2014)
  - Reduced-form
    - Direct modeling of prices
    - Stochastic process (mean reversion, jumps)
    - Selected representatives: Lucia and Schwartz (2002), Gudkov and Ignatieva (2021)
  - Machine learning / advanced statistical techniques
    - Usage of advanced techniques without fundamental relationships (NARX-NN, LSTM, GRU, CNN, LEAR, LASSO)
    - Selected representative: Lago et al. (2018)
- For more detailed literature reviews see Deschatre et al. (2021) and Lago et al. (2021)

Second-Layer Hybrid Structural Model (SLSH)

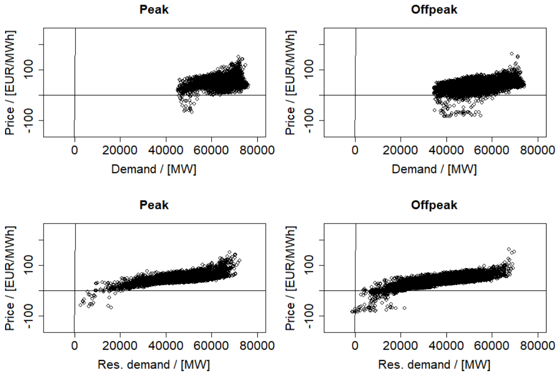
- We combine advantageous aspects in a hybrid structural model and recursively adopt the basic ideas on a deeper layer by asking:

  What drives the drivers of wholesale market prices?

- Central model components:

$$s_t = f_t(\hat{d}_t) + \sigma_t$$

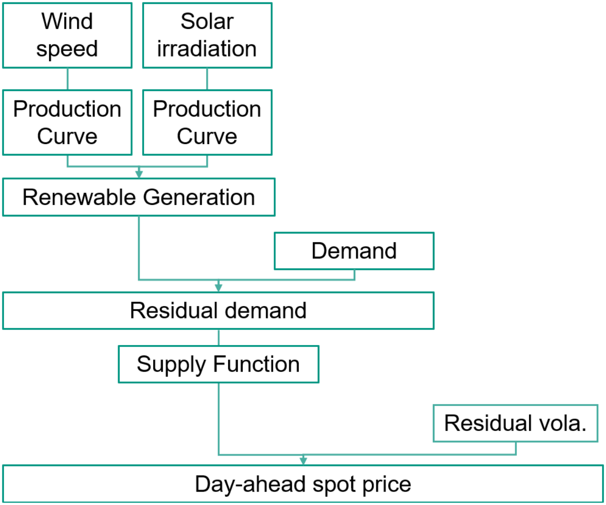
$$\hat{d}_t = d_t - re_t$$



s_t:	Day-ahead spot price
f_t:	Supply function
σ_t:	Residual volatility process
d_t:	Demand
$\hat{d}_t$:	Residual demand
re_t:	Renewable generation

Principle

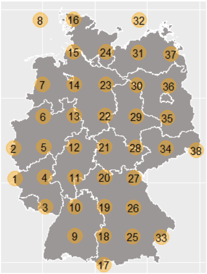
1. Weather variables
2. Empirical Production Curve
3. Demand
4. Supply Function
5. Residual volatility



Data Basis

Model Component	Time	Source
Solar irradiation	01.01.1990 - 31.12.2018	Anemos (2019)
Wind speed	01.01.1990 - 31.12.2018	Anemos (2019)
Demand	01.01.2017 - 31.12.2018	ENTSO-E (2022)
Wind energy infeed	01.01.2017 - 31.12.2018	ENTSO-E (2022)
PV energy infeed	01.01.2017 - 31.12.2018	ENTSO-E (2022)
PV and wind capacity	31.12.2016 - 31.12.2018	Bundesnetzagentur (2019a), Bundesnetzagentur (2019b)
Day-ahead prices	01.01.2017 - 31.12.2018	EEX (2022)

Source: Netzentwicklungsplan (2022)



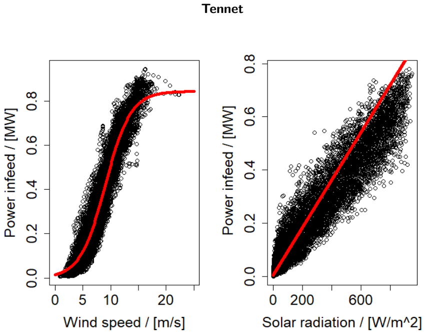
Weather Variables

- Modeling weather variable y (wind speed, solar irradiation) for technology u (wind, PV) in weather cell $k \in \{1, .., 38\}$ with VAR-model
- Removing local trends (seasonality) and using empirical (cumulative) distribution function (non-normality)
- Wind speed:
  - Time-dependent, site-specific volatility function
  - Empirical distribution function varying across seasons
- Solar irradiation:
  - Modeling daily maximum irradiation level
  - Deterministic pattern for intraday variation (following Morales et al. (2010) and Wagner (2014))
- Calculating a representative weather variable z for each of the $n \in \{1, .., 4\}$ balancing areas by weighting y with the respective installed capacity in each weather cell k

Empirical Production Curve

- Link between weather variables and renewable generation
- Motivated by technology specific shapes of production curves, we use a logistic function for wind and a second-order polynomial for PV
- We estimate the parameter vector $\Theta^{u,n}$ by means of the following minimization:

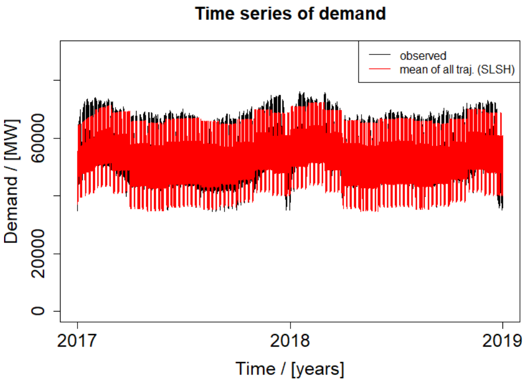
$$\min_{\Theta^{u,n},} \sum_{t \in T} \left(\hat{re}_t^{u,n} - \hat{g}^{u,n} \left(z_t^{u,n}, \Theta^{u,n} \right) \right)^2$$



$\Theta^{u,n}$:	Vector of parameters in production function g
$\hat{re}_t^{u,n}$:	Renewable infeed in balancing area n
$\hat{g}^{u,n}$:	Production function in balancing area n
$z_t^{u,n}$:	Representative/capacity weighted weather variable in balancing area n

Demand

- We follow Burger et al. (2004) and model demand with a flexible deterministic trend function with indicator variables for months, hours, weekends, holidays and winter season paired with a SARIMA $(2,0,2)\text{x}(1,0,1)_{24}$ component



Supply Function (1/2)

- Translation of market conditions into market clearing day-ahead price
- Considerable differences between peak and off-peak hours and seasonal patterns with regard to the shape (i.e. $s_t < 0$)
- We estimate monthly ($m \in \{1, .., 12\}$) supply functions $f_{t,m}$ for peak and for off-peak hours:

$$f_{t,m}(\hat{d}_{t_m}) = \min(s_{max}, \max(s_{min}, c_{t,m}(\hat{d}_{t_m}))$$

- For $c_{t,m}(\hat{d}_{t_m})$ we use the functional form of monthly, cubic smoothing splines for peak ($t_m \in T_m^{peak}$) and off-peak hours ($t_m \in T_m^{offpeak}$):

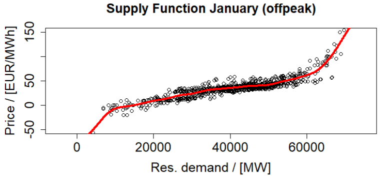
$$\sum_{t_m}(s_{t_m} - c_{t,m}(\hat{d}_{t_m}))^2 + \lambda_m \int (\frac{d^2 c_{t,m}(\hat{d}_{t_m})}{d\hat{d}_{t_m}^2}) dt_m$$

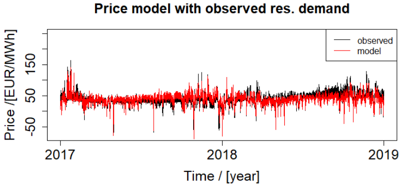
Price limits are set exogenously by EEX (2022)

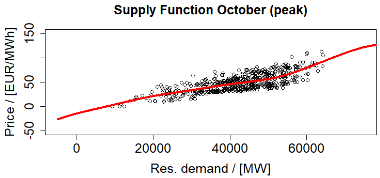
s_{max}: 3000 EUR/MWh
s_{min}: -500 EUR/MWh

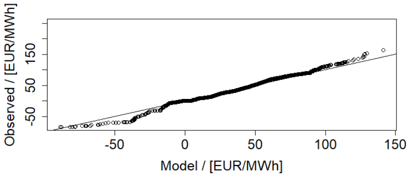
Supply Function (2/2)

	df	λ	Adj. R^2
Jan. (off-peak)	18.65	$1.15 \cdot 10^{-7}$	0.88
Oct. (peak)	6.22	$1.51 \cdot 10^{-5}$	0.56







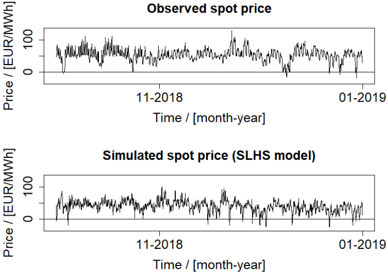


Residual Volatility

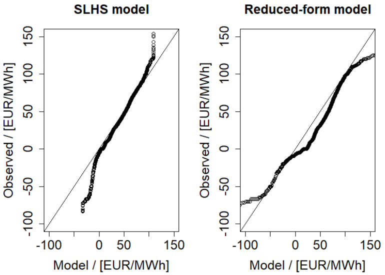
- Residual process $\sigma_t := f(\hat{d}_t) - s_t$ accounts for fundamentally unexplained variation (e.g. import/export, power plant outages, market psychology)
- We follow Burger et al. (2004) and model the residuals σ_t by means of a parsimonious time series model
- Inspection of σ_t reveals serial correlation at various lags and heteroscedasticity prompting us to choose an ARIMA process with GARCH noise: SARIMA $(2,0,2)x(1,0,1)_{24}$ with t-distributed error terms

Simulation (1/2)

- We simulate $N = 1000$ trajectories (weather variables, market wide demand, residual volatility)
- We investigate the capability of reproducing salient statistical features on one trajectory:



- We compare model-implied and observed spot prices and use a standard reduced-form price model (flexible trend function, mean-reversion component, spike process) inspired by Benth et al. (2013)

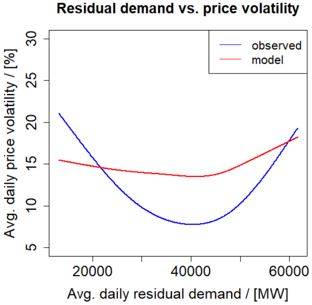


Simulation (2/2)

- We compare time series correlations of renewable generation from solar, wind, demand, and resiudal demand with spot prices
- Model-implied correlations are close to what we actually observe

	model	data
ρ_{s_t, re_t^w}	-0.46	-0.46
ρ_{s_t, re_t^s}	-0.09	-0.04
ρ_{s_t, d_t}	0.45	0.47
$\rho_{s_t, \hat{d}_t}$	0.79	0.77

- We calculate daily average values for price volatility and residual demand $\rightarrow$ higher price volatility levels for higher residual demand levels and reversal for very low residual demand levels



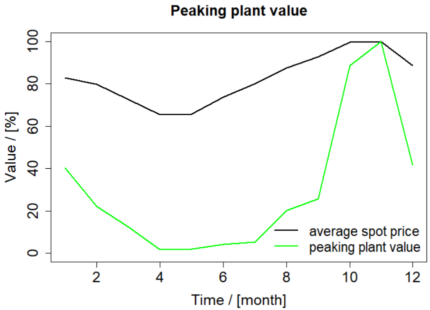
Peaking Power Plant

- Stylized profit margin of a peaking power plant as strip of call options:

$$rv_T^{pp}(c) = \sum_{t \in T} \max(s_t - c)^+$$

- Value of the basket of option contracts:

$$v_{t_0}(c) = \mathbb{E}_{t_0}^{\mathbb{Q}}[rv_T^{pp}(c)]$$



Additional assumptions:

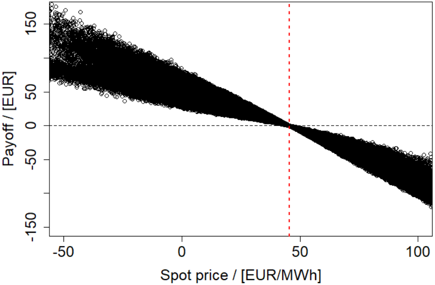
- Ignoring risk premia and using physical measure $\mathbb{P}$
- Variable cost (gas): $c = 60$ EUR/MWh
- Risk free rate (discounting): $r_f = 0.2\%$

Load Serving Entity

- Simplified revenue stream for load serving entities (lse):

$$rv_T^{lse}(p) = \sum_{t \in T} \hat{q}_t (p - s_t)$$

Load serving contract (payoff)



$$\mathbb{E}_{t_0}^{\mathbb{Q}} rv_T^{lse}(p) = 0$$

$$\mathbb{E}_{t_0}^{\mathbb{Q}} s_t = 44.27 < p = 45.50 \ EUR/MWh$$

Scenario Analysis of Renewable Capacities

$+$ 2.2 GW wind offshore
$+$ 1.7 GW wind onshore

in equally distributed (A) and clustered (B) manner

Peaking Power Plant:

	base	scenario A	scenario B
$v_{t_0}(c = 60)$	1.20	1.12	1.09
% *increase*	-	-6.87%	-9.49%

Yearly Δv_{t_0} of a power plant (500 MW):

$500\ MW \cdot (1.12 - 1.09)\ EUR/MWh \cdot 8760\ h = 131,400\ EUR$

Load Serving Entity:

	base	scenario A	scenario B
p	45.50	44.67	44.34

Electricity cost difference (e.g. 150 MW/hour):

$150\ MW \cdot (44.67 - 44.34)\ EUR/MWh \cdot 8760\ h = 433,620\ EUR$

Summary and Outlook

- Flexible modeling framework capable of incorporating local aspects of renewables and reproducing salient features
- Once calibrated, different scenarios, a concrete price time series, price distributions and real option values can be derived
- Model framework allows to quantify the distinct impact of local changes in renewable generation portfolio on wholesale market prices and helps to guide hedging, investment and political decisions considering changes in the market
- Modification of supply curve methodology considering further elements (i.e. fuels, market coupling) while obtaining merit order induced shape
- Out-of-sample testing for mid-term hedging horizons and testing performance during pandamic and military conflict

Bibliography I

Anemos (2019). *Wind Atlas and Production Index Europe: Commercial Supplier of Weather Data for Wind Power Applications*. Anemos Gesellschaft für Umweltmeteorologie mbH.

Benth, Fred, Jan Kallsen, and Thilo Mayer-Brandis (2007). "A Non-Gaussian Ornstein-Uhlenbeck Process for Electricity Spot Price Modeling and Derivatives Pricing". In: *Applied Mathematical Finance* 14, pp. 153–169.

Benth, Fred Espen, Richard Biegler-König, and Rüdiger Kiesel (2013). "An Empirical Study of the Information Premium on Electricity Markets". In: *Energy Economics* 36, pp. 55–77.

Bessembinder, Hendrik and Michael L Lemmon (2002). "Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets". In: *Journal of Finance* 57, pp. 1347–1382.

Bundesnetzagentur (2019a). *EEG-Registerdaten*. URL: https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/ErneuerbareEnergien/ZahlenDatenInformationen/EEG_Registerdaten/start.html.

Bundesnetzagentur (2019b). *Marktstammdatenregister*. URL: https://www.marktstammdatenregister.de/MaStR.

Burger, Markus et al. (2004). "A Spot Market Model for Pricing Derivatives in Electricity Markets". In: *Quantitative Finance* 4, pp. 109–122.

Deschatre, Thomas, Olivier Féron, and Pierre Gruet (2021). "A Survey of Electricity Spot and Futures Price Models for Risk Management Applications". In: *Energy Economics* 102, p. 105504.

EEX (2022). *EEX-Transparency*. URL: https://www.eex-transparency.com/.

Bibliography II

ENTSO-E (2022). *ENTSOE-E Transparency Platform*. URL: https://transparency.entsoe.eu/.

Eydeland, Alexander and Krzysztof Wolyniec (2003). *Energy and Power Risk Management: New Developments in Modeling, Pricing, and Hedging*. Wiley Finance.

Gudkov, Nikolay and Katja Ignatieva (2021). "Electricity Price Modelling with Stochastic Volatility and Jumps: An Empirical Investigation". In: *Energy Economics* 98, p. 105260.

Lago, Jesus, Fjo De Ridder, and Bart De Schutter (2018). "Forecasting Spot Electricity Prices: Deep Learning Approaches and Empirical Comparison of Traditional Algorithms". In: *Applied Energy* 221, pp. 386–405.

Lago, Jesus et al. (2021). "Forecasting Day-Ahead Electricity Prices: A Review of State-of-the-Art Algorithms, Best practices and an Open-Access Benchmark". In: *Applied Energy* 293, p. 116983.

Lucia, Julio J. and Eduardo S Schwartz (2002). "Electricity Prices and Power Derivatives: Evidence from the Nordic Power Exchange". In: *Review of Derivatives Research* 5, pp. 5–50.

Meyer-Brandis, Thilo and Peter Tankov (2008). "Multi-Factor Jump-Diffusion Models of Electricity Prices". In: *International Journal of Theoretical and Applied Finance* 11, pp. 503–528.

Morales, Juan M., Roberto Minguez, and Antonio J. Conejo (2010). "A Methodology to Generate Statistically Dependent Wind Speed Scenarios". In: *Applied Energy* 87, pp. 843–855.

Netzentwicklungsplan (2022). *Netzentwicklungsplan*. URL: https://www.netzentwicklungsplan.de.

Wagner, Andreas (2014). "Residual Demand Modeling and Application to Electricity Pricing". In: *The Energy Journal* 35.