

Recent advances in electricity price forecasting: A MMXXII (i.e., 2022) perspective

Rafał Weron*

Department of Operations Research and Business Intelligence
Wrocław University of Science and Technology (PWr), Poland
<http://kbo.pwr.edu.pl/en/staff/rafal-weron/>



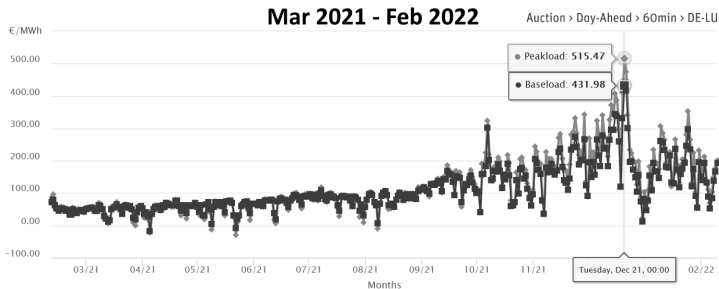
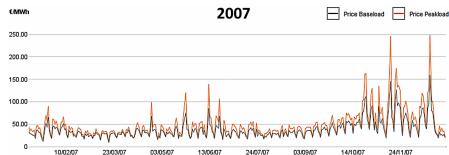
*Based on joint work with K.Hubicka, A.Jędrzejewski, K.Maciejowska, G.Marcjasz, J.Nasiadka, W.Nitka, T.Serafin, B.Uniejewski (PWr), J.Lago (Amazon), J.Nowotarski (BNY Mellon), C.Kath, M.Narajewski, F.Ziel (Essen), C.Challu, K.Olivares (Carnegie Mellon)

THE WORLD IS CHANGING ...

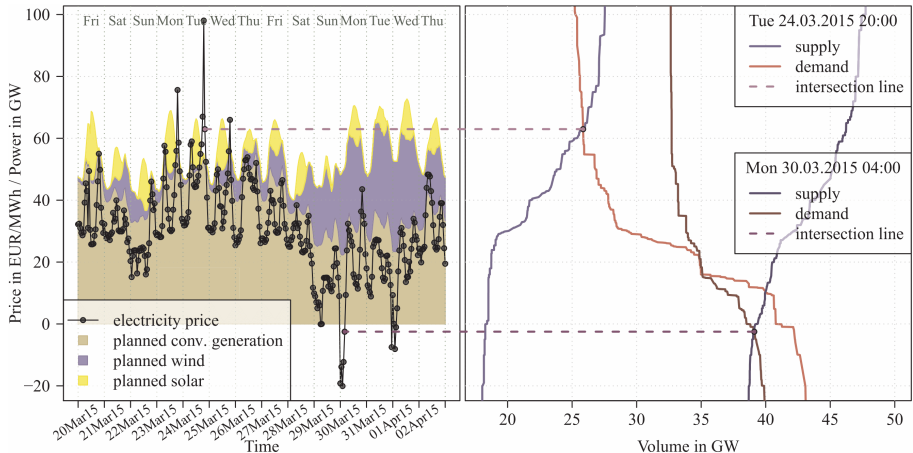


The power markets are changing ...

Here: 2007 vs. 2017 vs. 2021/22 average daily EPEX prices for Germany



... in particular due to increased wind ...

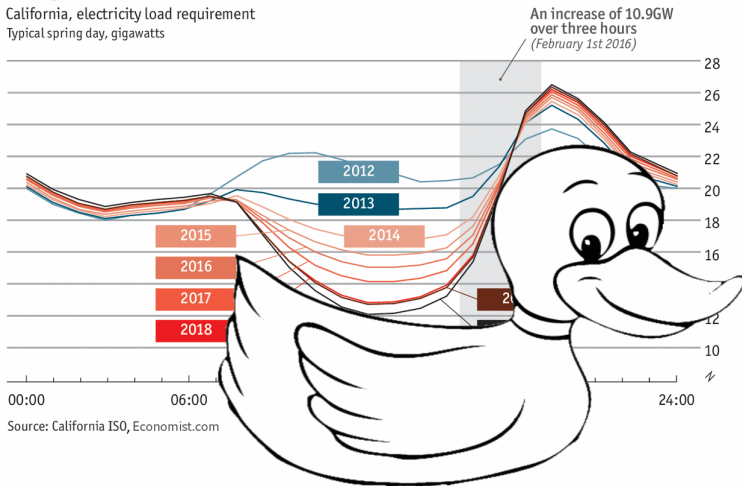


Source: Ziel & Steinert (2018, RSER)

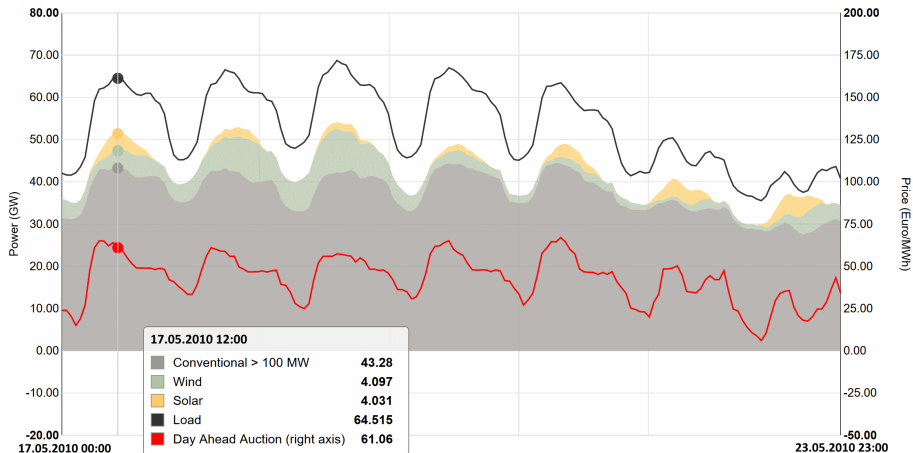
... and solar penetration

Who gets the bill?

California, electricity load requirement
Typical spring day, gigawatts

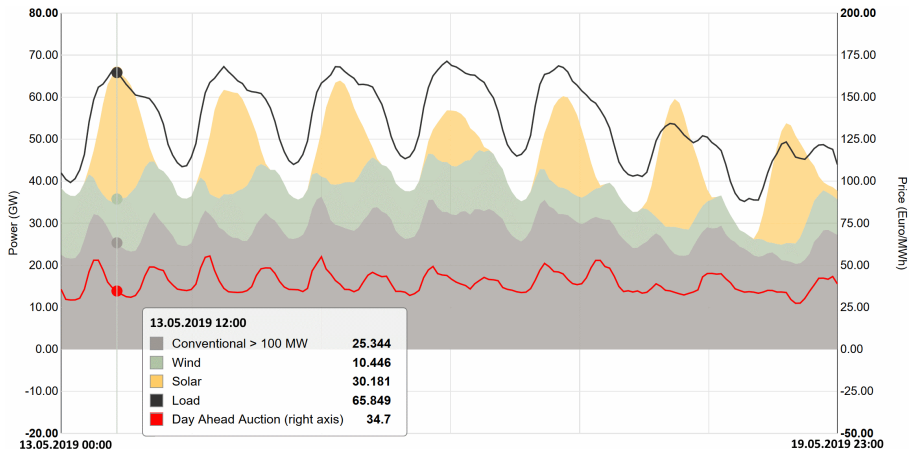


Germany 2010: No ducks



Source: www.energy-charts.de

Germany 2019: 'Duck curve' (or 'peak shaving')



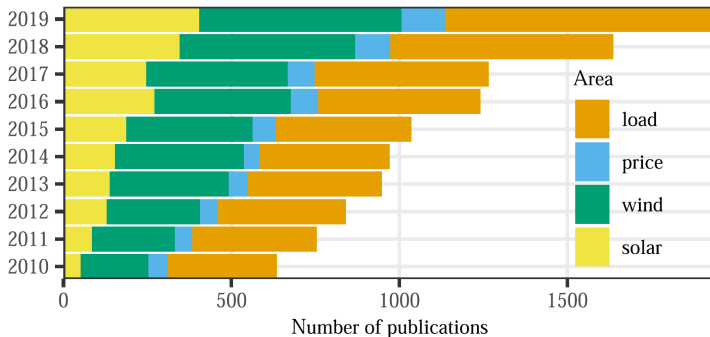
Source: www.energy-charts.de

But the (Academic) Empire ...



Load, price, wind & solar forecasting*

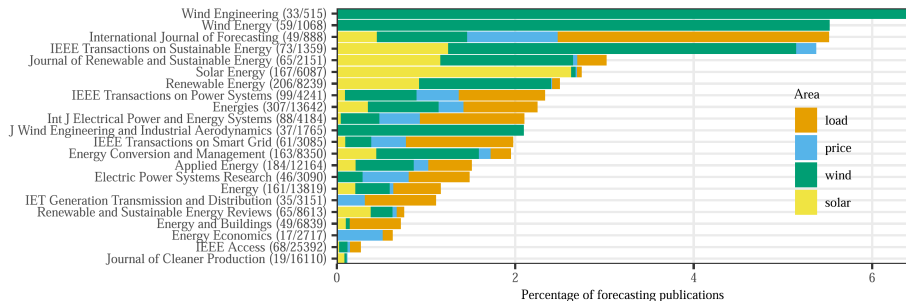
(Hong, Pinson, Wang, Weron, Yang & Zareipour, 2020, IEEE OAJPE)



* Scopus indexed

Percentage of energy forecasting publications*

(Hong, Pinson, Wang, Weron, Yang & Zareipour, 2020, IEEE OAJPE)

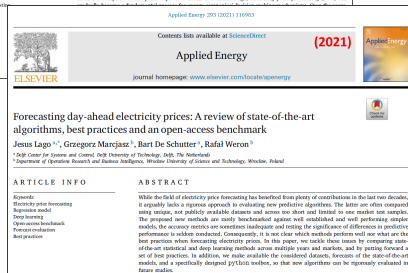
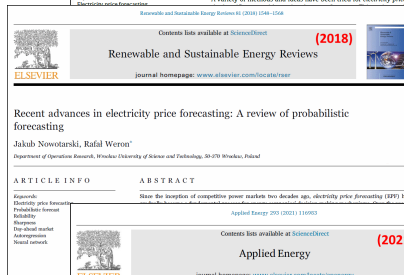


* Top 10 journals in each area (2010-2019); some are ranked top 10 across multiple areas

** Numbers of forecasting/total publications for each journal are shown in parentheses

Agenda

- 1 Intro (a bit lengthy)
- 2 Model evolution
 - Models and tweaks
 - Regularization
 - Going deep
- 3 Calibration windows
 - Averaging
 - Identifying breakpoints
- 4 Beyond point forecasts
 - Probabilistic
 - Path (ensemble)
- 5 Financial evaluation
 - Euros not errors



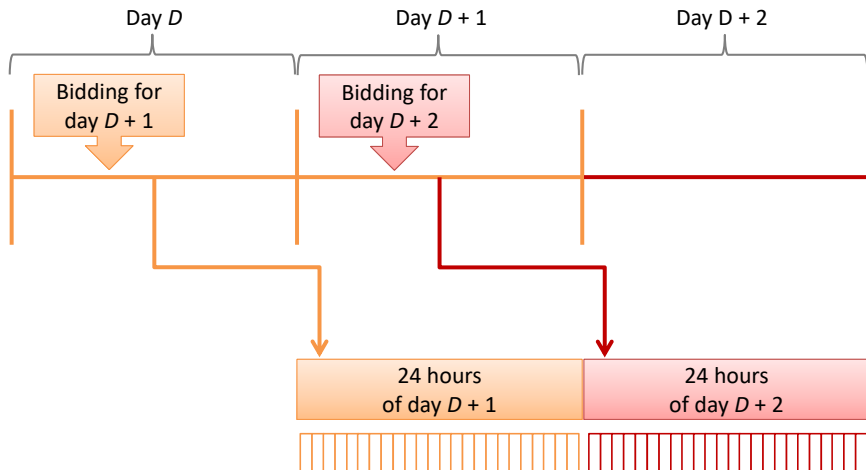
Why forecast electricity spot prices?

- Risk is managed against **recourse to the spot markets**
- Forward prices are assessed **based on spot price forecasts**, adjusted by risk premia
 - Electricity is non-storable → no physical cost-of-carry theory
- The workhorse of European trading is the **day-ahead market**



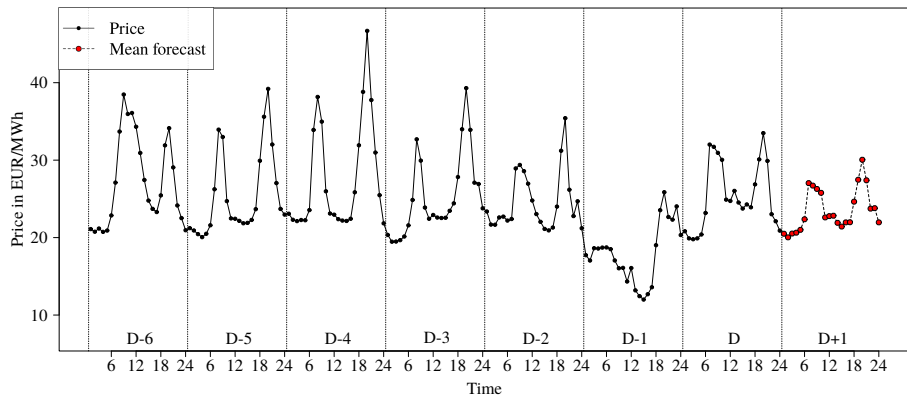
The workhorse of European power trading

The day-ahead market (> 90% of papers)

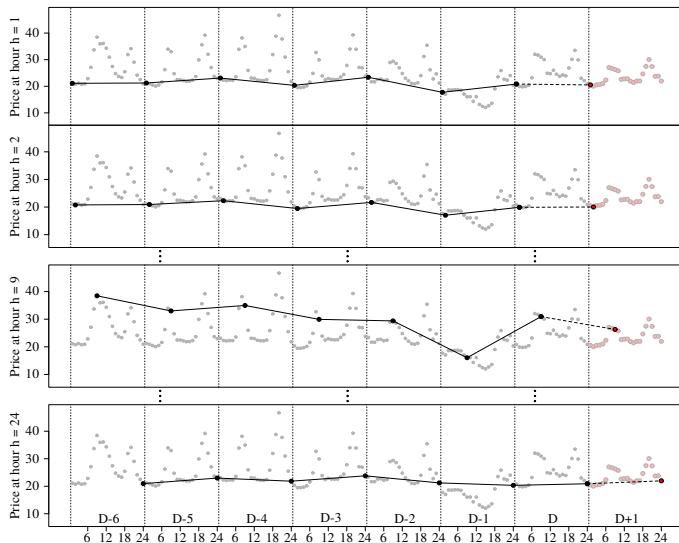


Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)



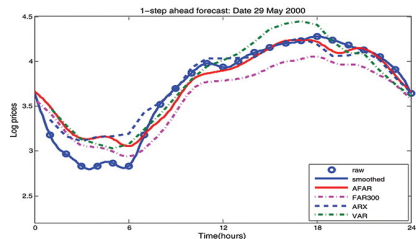
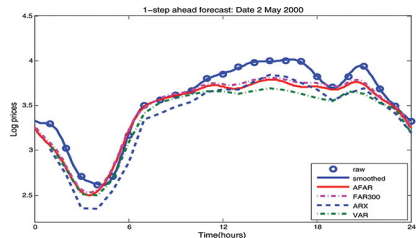
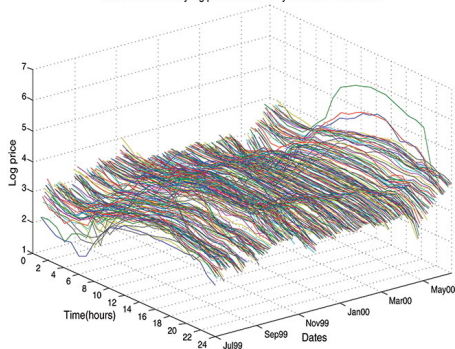
... multivariate ...



... or functional (data analysis)?

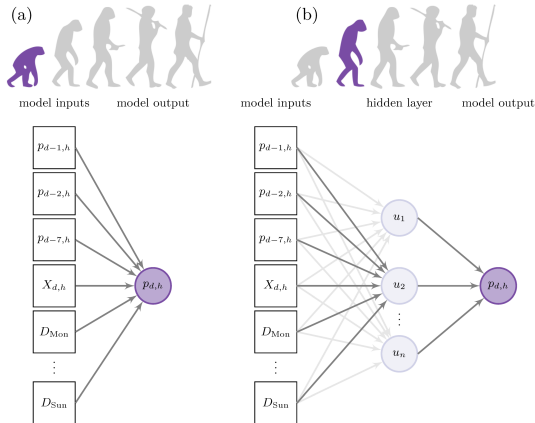
(Chen & Li, 2017, JBES; Chen et al., 2019, Ann.Appl.Stat.)

Smoothed electricity log price curves 5 July 1999—11 June 2000



Which modeling framework?

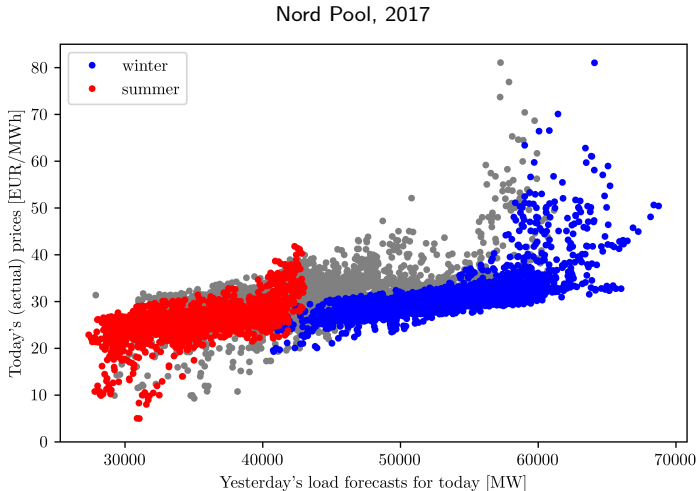
(Jędrzejewski, Lago, Marcjasz & Weron, 2022, IEEE-PEM)



Early EPF models: **(a)** linear regression and **(b)** a single-output shallow neural network

Why nonlinear?

(Jędrzejewski, Lago, Marcjasz & Weron, 2022, IEEE-PEM)



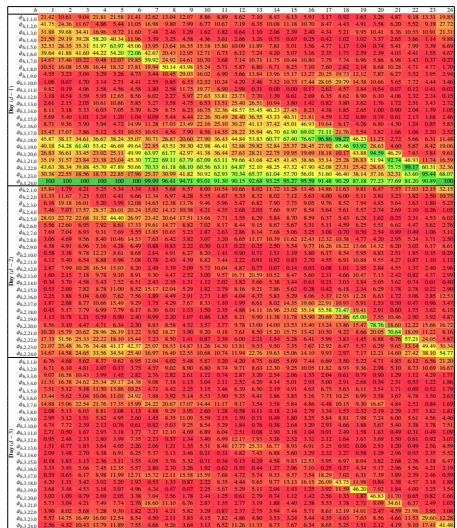
(Uniejewski et al., 2016, Energies; Ziel, 2016, IEEE-TPWRS; Ziel & Weron, 2018, ENEECO)

Minimize the residual sum of squares (RSS) + a penalty:

$$\hat{\beta} = \underset{\beta_j}{\operatorname{argmin}} \left\{ \text{RSS} + \lambda \sum_{j=1}^n |\beta_j|^q \right\}$$

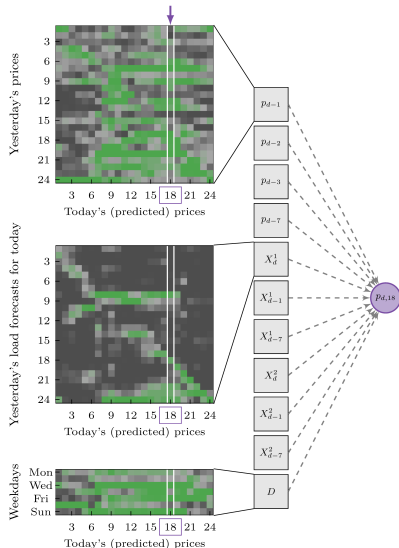
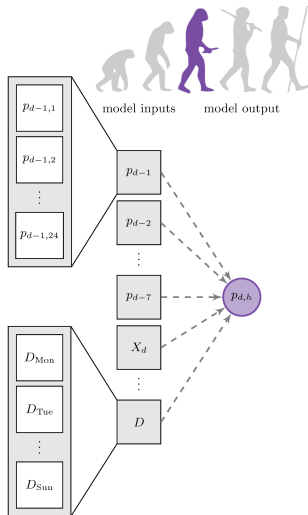
Blue areas – constraint regions, e.g., $|\beta_1| + |\beta_2| \leq t$

Red ellipses – contours of the LS error function



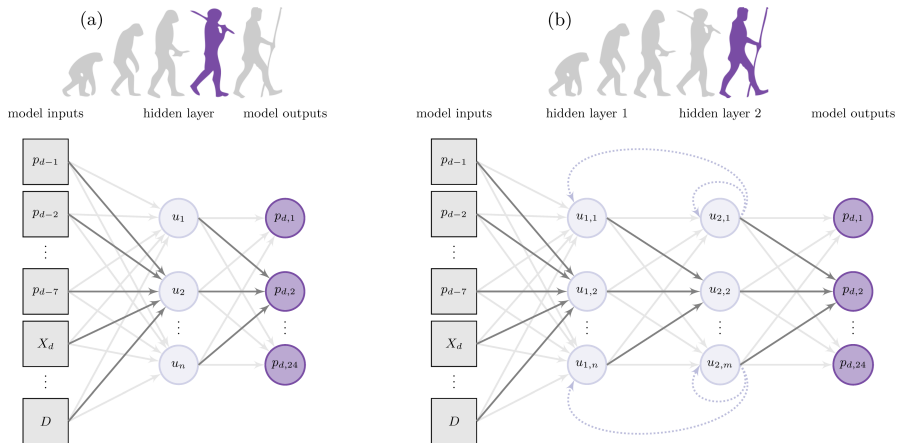
LASSO-Estimated AR (LEAR)

(Lago et al., 2021, APEN; Jędrzejewski et al., 2022, IEEE-PEM)



Multi-output and deep neural networks (DNNs)

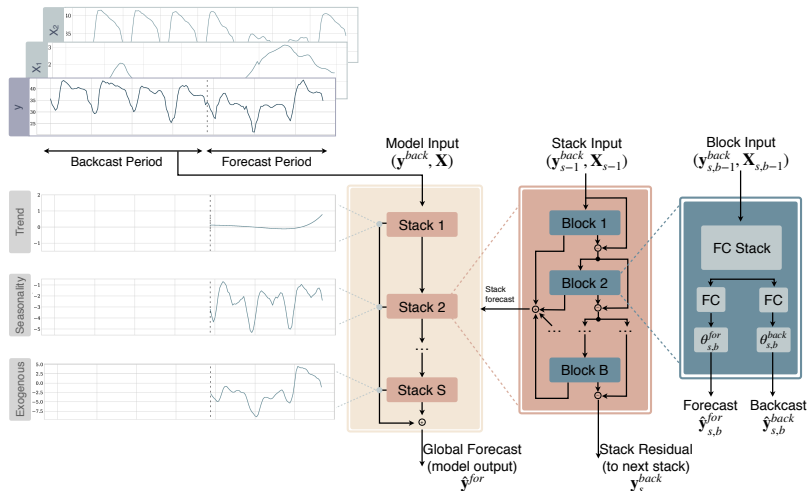
(Lago et al., 2021, APEN; Jędrzejewski et al., 2022, IEEE-PEM)



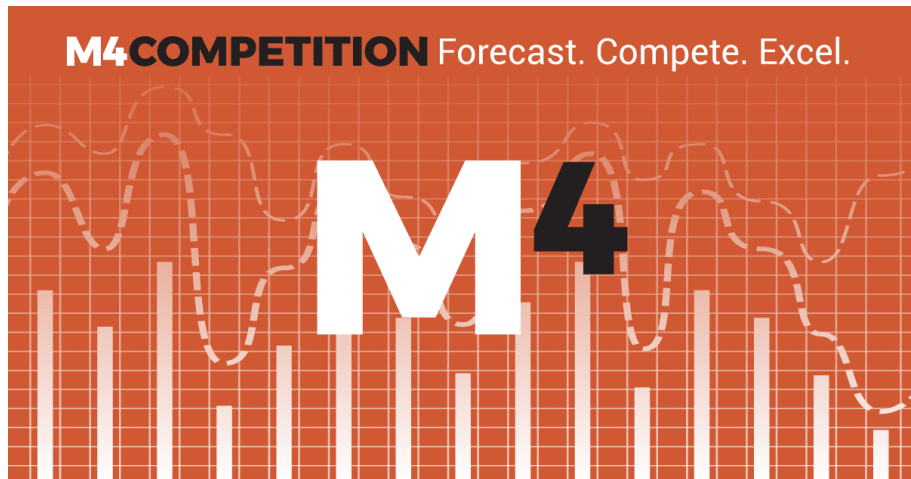
Multi-output NN architectures: **(a)** shallow and **(b)** deep with 2 hidden layers

Interpretable NNs: NBEATSx

(Olivares, Challu, Marcjasz, Weron & Dubrawski, 2021, WP)



What do the experts have to say?



Why bother with ML?



Spyros Makridakis @spyrosmakrid · 8 Jun 2018



2a/ The Combination of approaches was the king of the M4. Out of the 17 most accurate methods, 12 were Combinations of mostly statistical ones.



Spyros Makridakis @spyrosmakrid · 8 Jun 2018



5/ The five Machine Learning (ML) methods submitted in the M4 performed poorly, none of them being more accurate than the statistical benchmark and only one being more accurate than Naïve 2, finding consistent with our PLOS paper



Spyros Makridakis @spyrosmakrid · 8 Jun 2018



6/ The above findings suggest that individual statistical or ML methods are of limited value and that hybrid approaches and a combination of methods exploiting advantages and minimizing shortcomings is the way forward to improve f/casting accuracy and make f/casting more valuable

- Makridakis et al. (2018, PLoS ONE; 2018, IJF)

Really?

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(2021)



Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark

Jesus Lago^{a,*}, Grzegorz Marcjasz^b, Bart De Schutter^a, Rafał Weron^b^a Delft Center for Systems and Control, Delft University of Technology, Delft, The Netherlands^b Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology, Wrocław, Poland

ARTICLE INFO

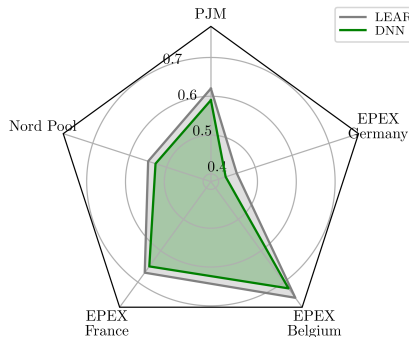
Keywords:

Electricity price forecasting
Regression model
Deep learning
Open-access benchmark
Forecast evaluation
Best practices

ABSTRACT

While the field of electricity price forecasting has benefited from it arguably lacks a rigorous approach to evaluating new prediction using unique, not publicly available datasets and across too short time horizons. The proposed new methods are rarely benchmarked against well-established models, the accuracy metrics are sometimes inadequate and test performance is seldom conducted. Consequently, it is not clear what are the best practices when forecasting electricity prices. In this paper, we review the state-of-the-art statistical and deep learning methods across multiple datasets, set of best practices. In addition, we make available the considered models, and a specifically designed python toolbox, so that new studies can be conducted.

rMAE (relative to a naive forecast)

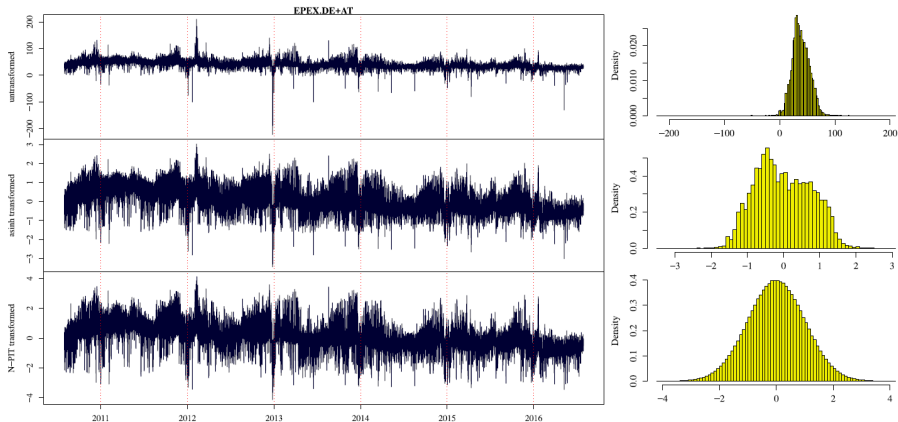


Dealing with asymmetry and heavy tails

(Uniejewski, Weron & Ziel, 2018, IEEE-TPWRS)

Variance stabilizing transformations (VSTs), e.g.,

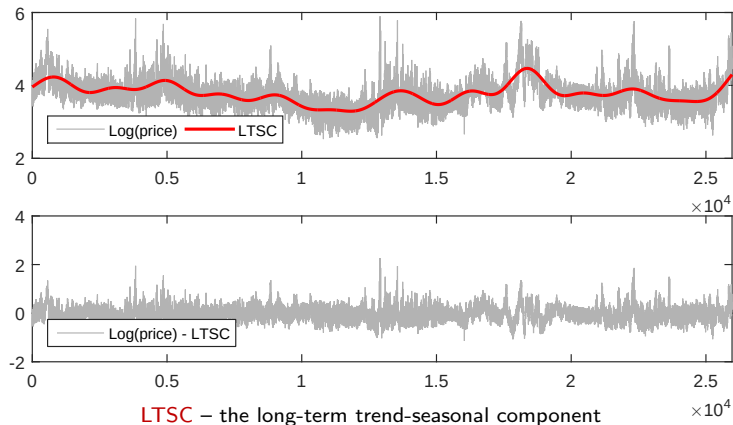
$$Y_{d,h} = \mathbf{asinh}(P_{d,h}) \equiv \log(P_{d,h} + \sqrt{P_{d,h}^2 + 1}) \text{ or } (\mathbf{N-})\mathbf{PIT}$$



What about seasonal decomposition?

(Nowotarski & Weron, 2016, ENEECO; Marcjasz et al., 2019, IJF)

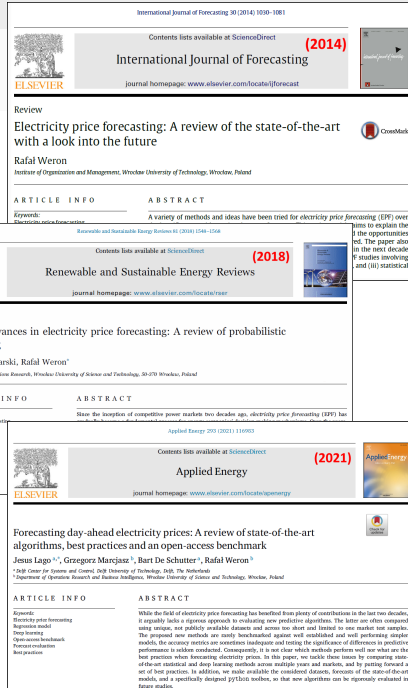
Decompose $\rightarrow$ predict the **LTSC** & residuals $\rightarrow$ combine



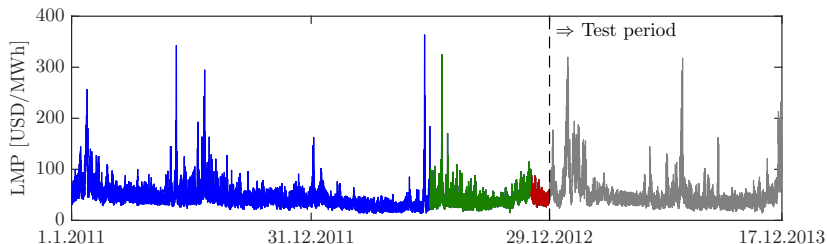
LTSC – the long-term trend-seasonal component

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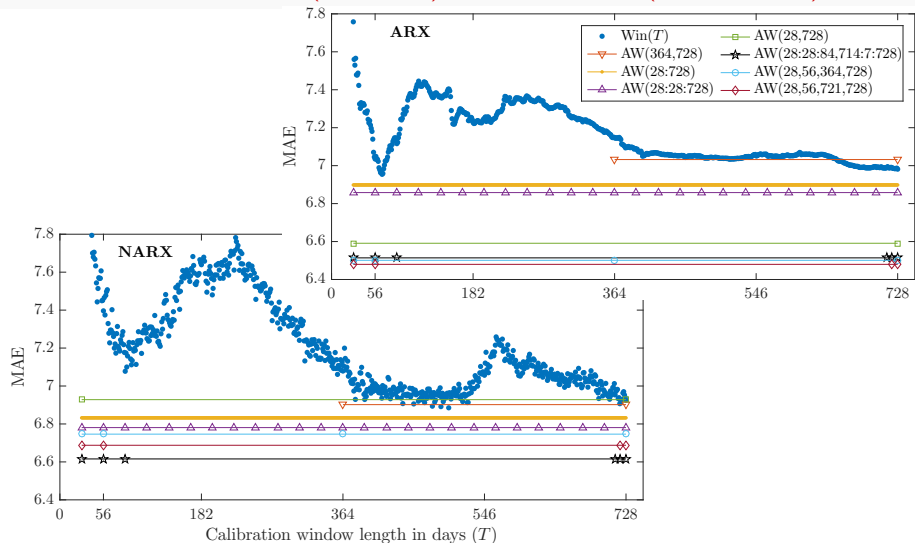
Searching for the optimal calibration window



- Which window length is optimal?
 - 728-day, 182-day, 56-day, ...
 - Longer – better reflect trends and yield more stable parameters
 - Shorter – adapt quicker to changes in the price behavior
- EPF literature: Typically selected ad-hoc
 - Ranging from 10 days to 6 years

Averaging across calibration windows

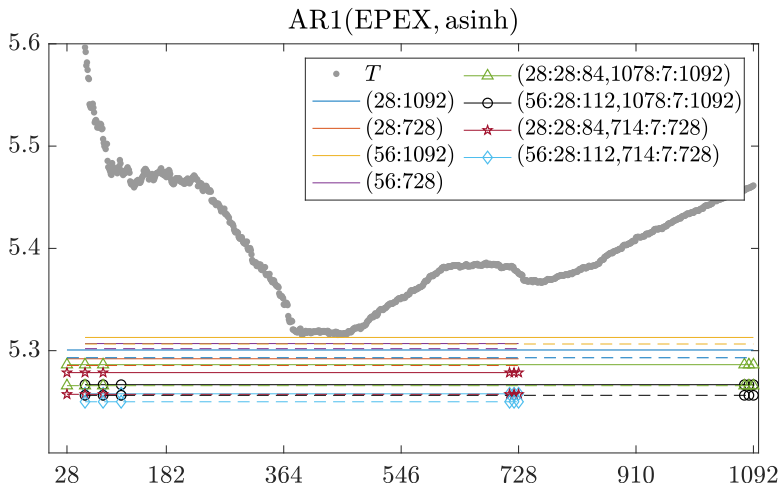
Structural breaks: Pesaran, Pick (2011, JBES); EPF: Hubicka et al. (2019, IEEE-TSE)



Past performance-weighted averaging

(Marcjasz, Serafin & Weron, 2018, Energies)

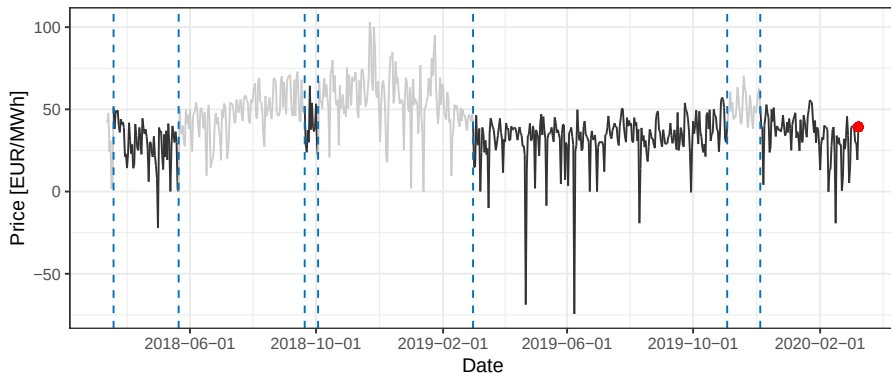
'—' AW, '- -' WAW



Detection of change/breakpoints

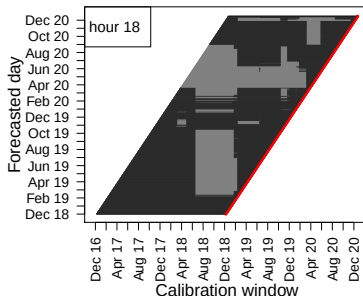
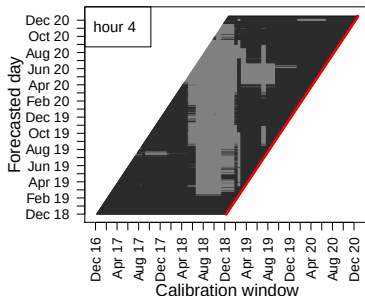
(de Marcos, Bunn, Bello & Reneses, 2020, *Energies*; Nasiadka, Nitka & Weron, ICCS 2022)

Breakpoints (blue) split the calibration window into similar (**black**) and remaining (= left out; **gray**) subperiods:



EPEX-DE: Narrowest-Over-Threshold (NOT)

NOT: Baranowski et al. (2019, JRSSB); EPF: Nasiadka et al. (ICCS 2022)

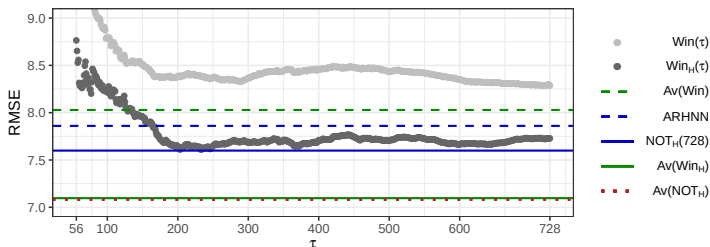
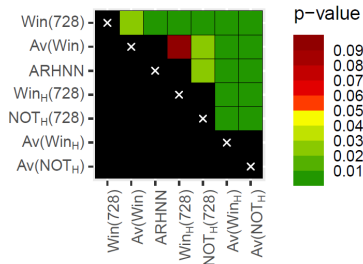


$$\begin{aligned}
 P_{d,h} = & \underbrace{\alpha_h D_d}_{\text{Dummies}} + \sum_{p \in \{1,2,7\}} \beta_{h,p} P_{d-p,h} + \underbrace{\theta_{h,1} P_{d-1,min} + \theta_{h,2} P_{d-1,max}}_{\text{Yesterday's price range}} \\
 & + \underbrace{\theta_{h,3} P_{d-1,24}}_{\text{Last known price}} + \underbrace{\theta_{h,4} \hat{L}_{d,h} + \theta_{h,5} \hat{W}_{d,h} + \theta_{h,6} \hat{S}_{d,h}}_{\text{Exogenous variables}} + \varepsilon_{d,h}
 \end{aligned}$$

EPEX-DE: RMSE errors & DM test

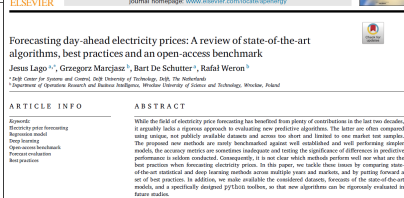
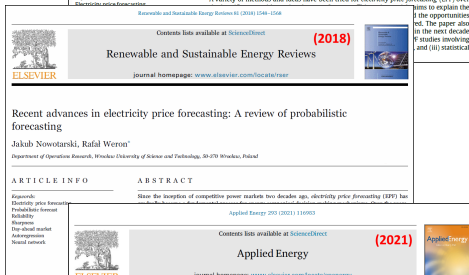
(Nasiadka, Nitka & Weron, ICCS 2022)

Method	RMSE
Win(728)	8.2860
Av(Win)	8.0286
ARHNN	7.8605
Win _H (728)	7.7286
NOT _H (728)	7.5994
Av(Win _H)	7.0968
Av(NOT _H)	7.0831



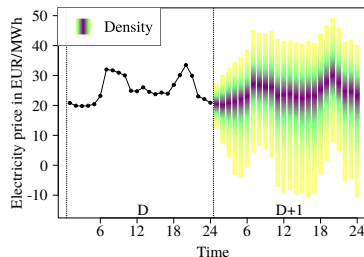
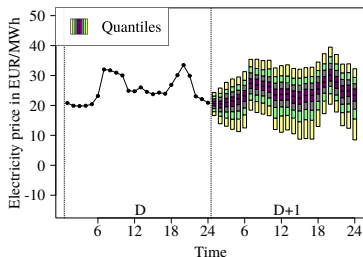
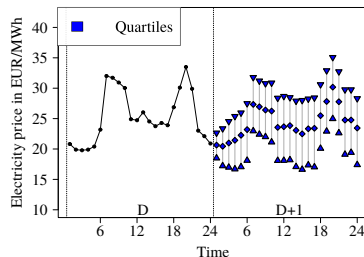
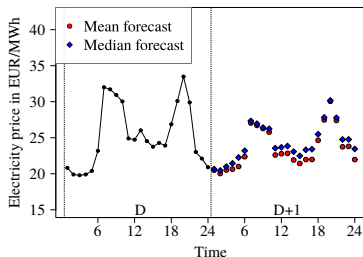
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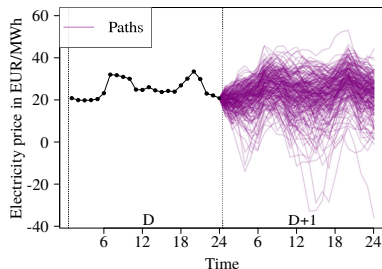
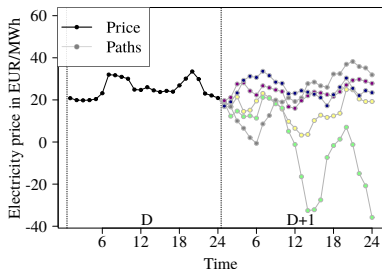


A new hype: Point $\rightarrow$ probabilistic forecasting

(< 10% of EPF papers)



Not yet a hype: Probabilistic $\rightarrow$ path forecasting



- Relatively novel in EPF (but not in weather forecasting)
- Operational decisions often depend on prices for neighboring hours (e.g., ramping costs of power plants)
- Regulatory incentives: in Germany a wind park can receive less subsidies if the electricity price is negative for 6 hours in a row

Recent reviews of probabilistic EPF



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

(2018)

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser



Recent advances in electricity price forecasting: A review of probabilistic forecasting



Jakub Nowotarski, Rafał Weron*

Department of Operations Research, Wrocław University of Science and Technology, 50-370 Wrocław, Poland

ARTICLE INFO

Keywords:

Electricity price forecasting
Probabilistic forecast
Reliability
Sharpness
Day-ahead market
Autoregression
Neural network



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(2018)

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser



Probabilistic mid- and long-term electricity price forecasting

Florian Ziel^{a,*}, Rick Steinert^b

^a Universität Duisburg-Essen, Berliner Platz 6-8, 45127 Essen, Germany

^b Europa-Universität Viadrina, Große Schärnstraße 59, 15230 Frankfurt, Oder, Germany



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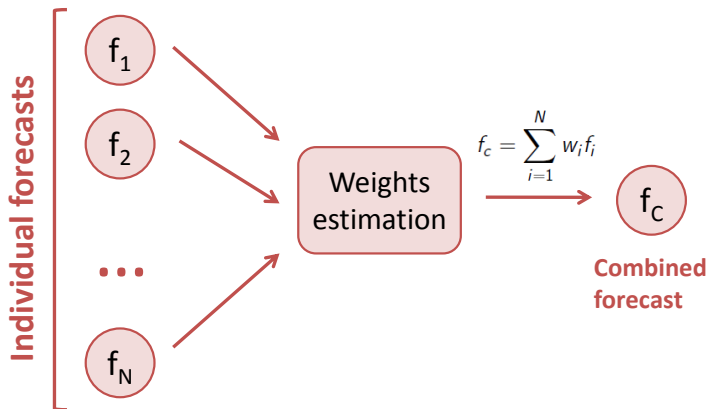
Keywords:

Electricity prices
Probabilistic forecasting

ABSTRACT

The liberalization of electricity markets and the development of renewable energy sources has led to new challenges for decision makers. These challenges are accompanied by an increasing uncertainty about future

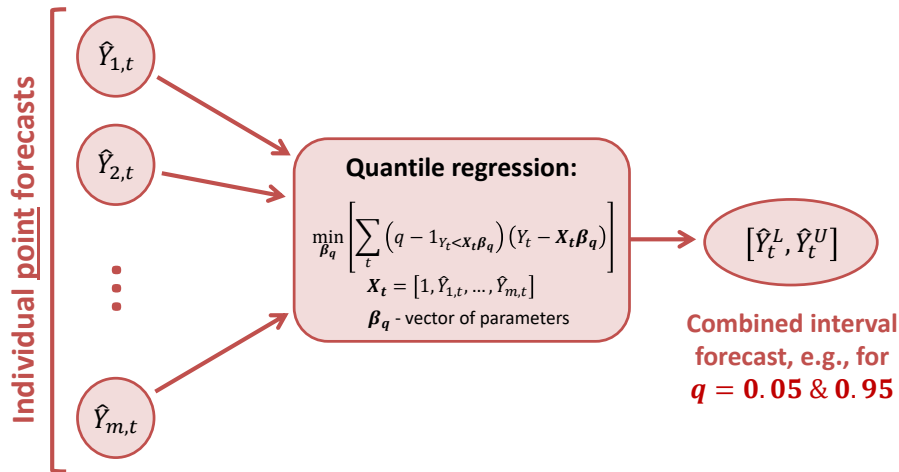
Point forecast averaging: The idea



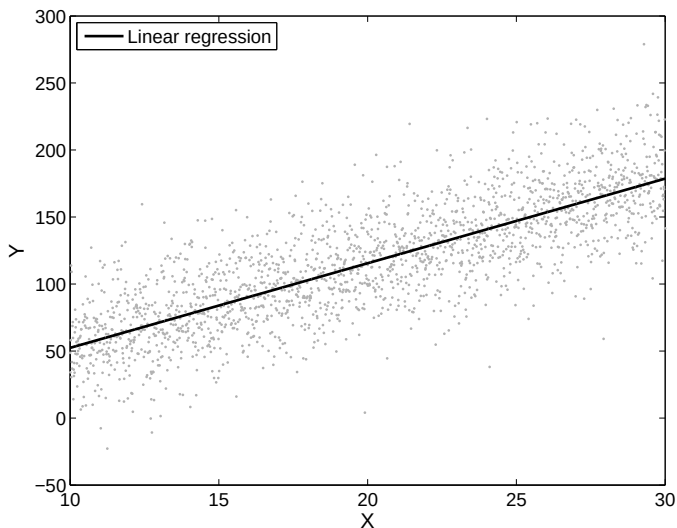
- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger

Quantile Regression Averaging: The idea

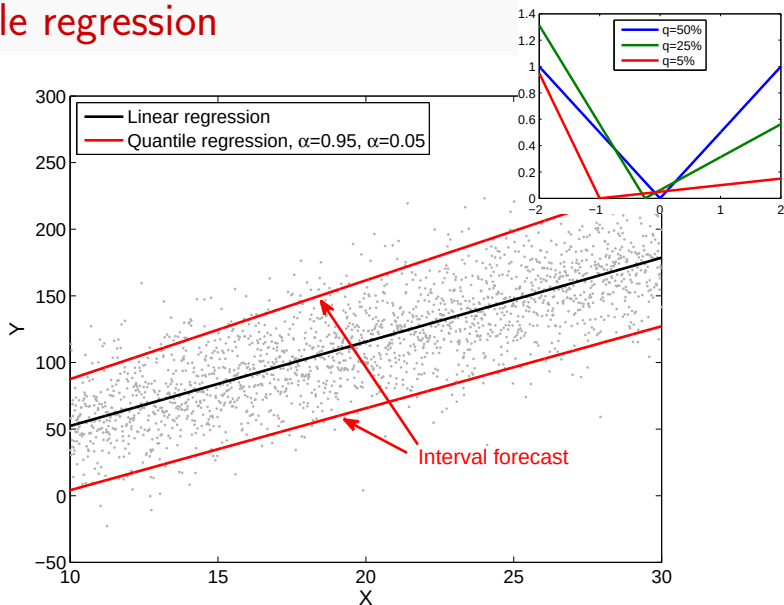
(Nowotarski & Weron, 2015, COST)



Quantile regression

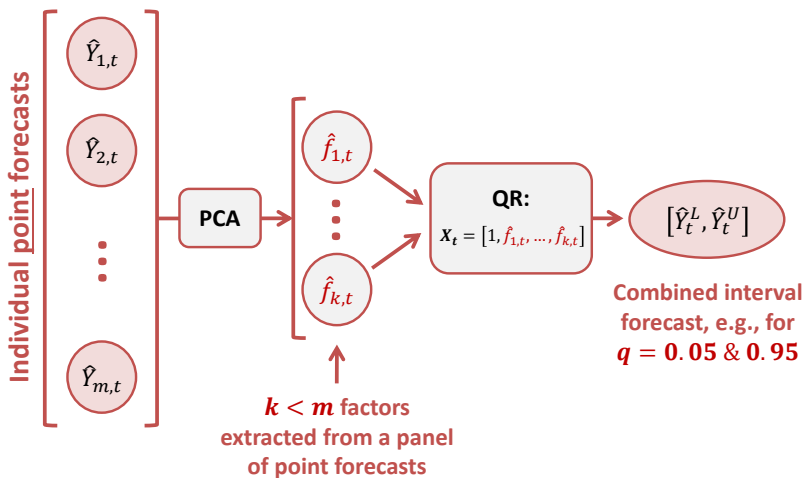


Quantile regression



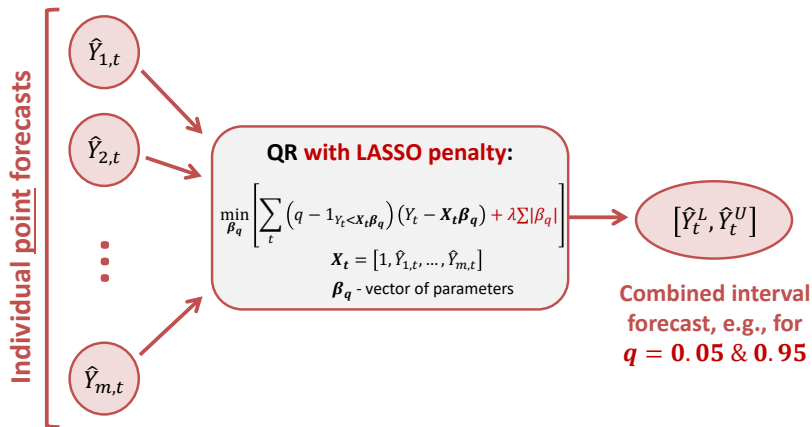
FQRA: When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



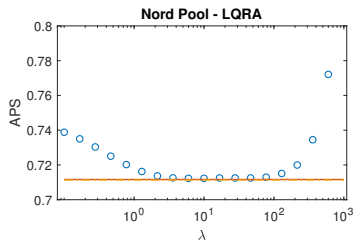
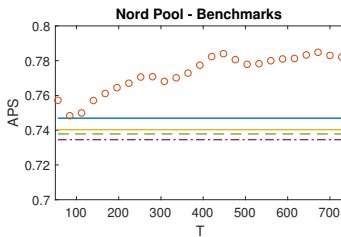
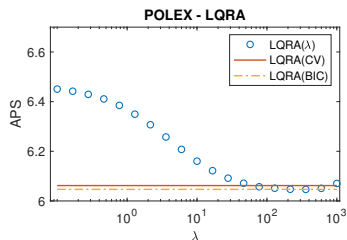
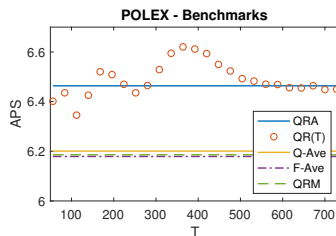
LASSO QRA (LQRA): An alternative to FQRA

(Uniejewski & Weron, 2021, ENEECO)



LQRA: Aggregate Pinball Scores (APS)*

(Uniejewski & Weron, 2021, ENEECO)

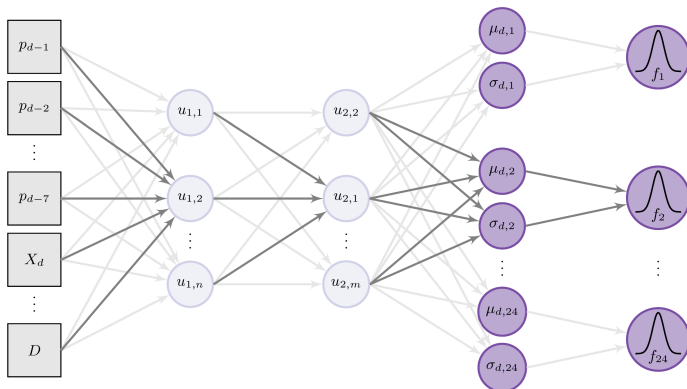


*Arithmetic averages over 99 percentiles and all hours in the test period

Probabilistic neural nets

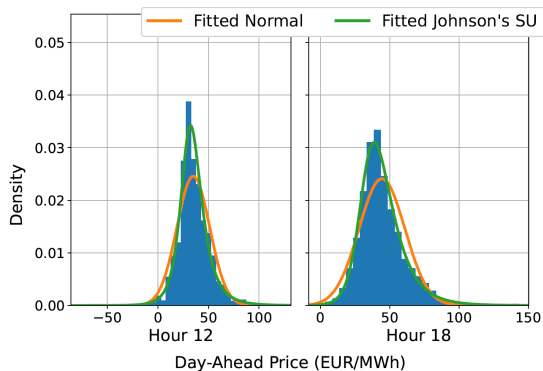
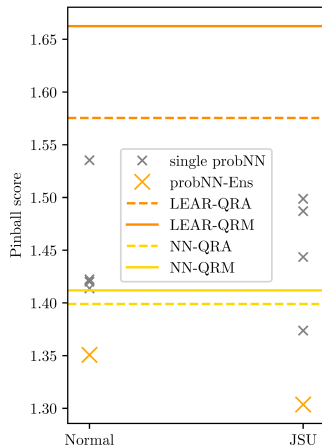
(Jędrzejewski et al., 2022, IEEE-PEM; Marcjasz, Narajewski, Weron & Ziel, 2022, WP)

model inputs hidden layer 1 hidden layer 2 distribution layer model output



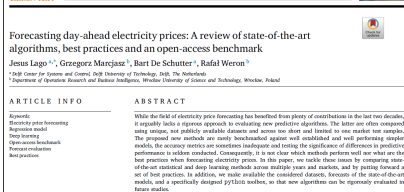
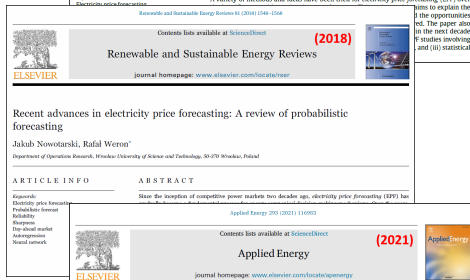
Perform surprisingly well ... after averaging

(Marcjasz, Narajewski, Weron & Ziel, 2022, WP)



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Hamidreza Zareipour, *Member, IEEE*, Claudio A. Cañizares, *Fellow, IEEE*, and Kankar Bhattacharya, *Senior Member, IEEE*

Index Terms—Demand-side management, economic benefit, economic value, forecasting error, price forecasting, scheduling.



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Christopher Kath^{a,*}, Florian Ziel^b

^aRWE Supply & Trading GmbH, Altenessenstr. 27, Essen 45141, Germany

^b University Duisburg-Essen, House of Energy Markets and Finance, Germany



energies

Article

(2020) **MDPI**

Christopher Kath ^{1,2} , Weronika Nitka ^{3,4} , Tomasz Serafin ^{3,4} , Tomasz Weron ^{3,4} ,
Przemysław Zaleski ^{3,5} and Rafał Weron ^{3,*}

¹ RWE Supply & Trading GmbH, 45141 Essen, Germany; christopher.kath@rwe.com

² House of Energy Markets and Finance, University of Duisburg-Essen, 45141 Essen, Germany

³ Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology.

50-370 Wrocław, Poland; weronikanitka@gmail.com (W.N.); tomaszserafin.96@gmail.com (T.S.);

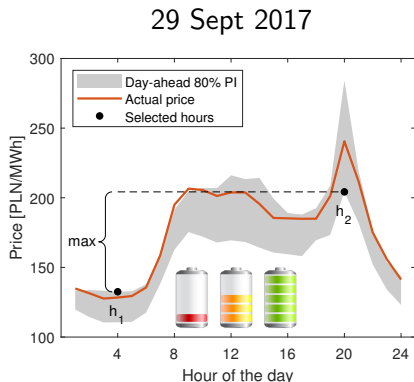
tomek.weron@gmail.com (TW); przemyslaw.zaleski@mwt.edu.pl (PZ)

net regression forecast model for German quarter-hourly electricity spot prices. In contrast to the intraday trading strategies based on the intraday continuous data, the intraday trading strategies based on the intraday discrete data are not been studied intensively with a clear focus on predictive power. In this paper, we check for the impact of early day-ahead (DA) EEXA prices on intraday trading strategies. The complementary discussion of economic benefits. A precise forecast of DA EEXA prices is utilized. We elaborate possible trading decisions based upon our forecasting results. We find that even simple electricity trading strategies impact if combined with a decent forecasting technique.

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Quantile-based trading strategies

(Uniejewski & Weron, 2021, ENEECO)



Simultaneously bid day-ahead:

- buy 1 MW for $\hat{P}_{d,h_1}^{1-\alpha}$ at hour h_1
- sell 0.8 MW at $\hat{P}_{d,h_2}^{\alpha}$ at hour h_2

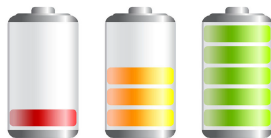
← With $\alpha = 10\%$ the spread is maximized for $\hat{P}_{d,4}^{90\%} = 133$ and $\hat{P}_{d,20}^{10\%} = 204$ PLN/MWh

- If bid(s) not accepted, settle in the balancing market

Quantile-based trading strategies: Results

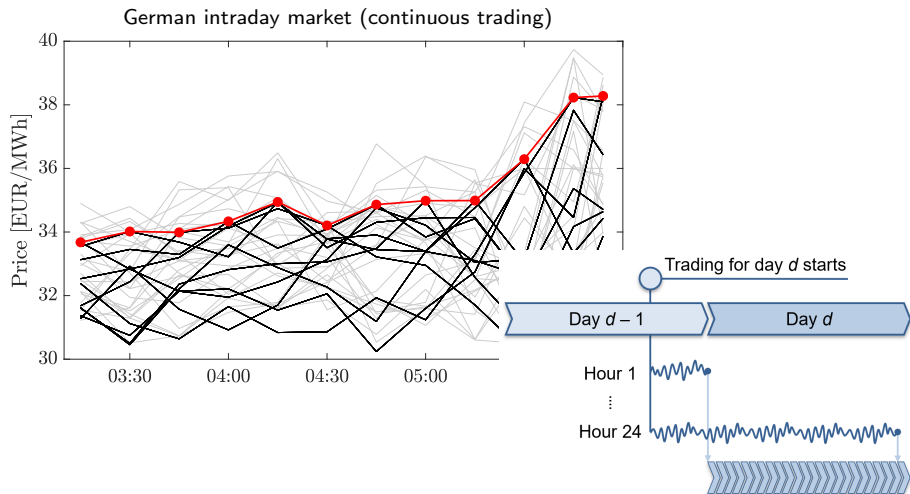
(Uniejewski & Weron, 2021, ENEECO)

Strategy			Profit		
Naive (4am–12pm)			33 065.29		
Point forecasts-based			37 722.39		
Quantile-based	1–99%	5–95%	10–90%	20–80%	25–75%
Q-Ave	41 317.92	43 328.89	43 432.31	43 289.09	43 033.88
F-Ave	39 848.26	43 369.44	44 052.04	44 088.11	43 130.34
QRM	41 163.29	43 054.28	43 124.12	43 731.54	42 240.25
LQRA(77)	42 360.05	44 135.49	44 713.52	44 684.40	43 624.65
LQRA(BIC)	42 886.10	43 993.23	44 502.81	45 396.21	42 741.57
LQRA(CV)	41 693.80	43 971.88	44 238.45	45 073.19	43 103.88



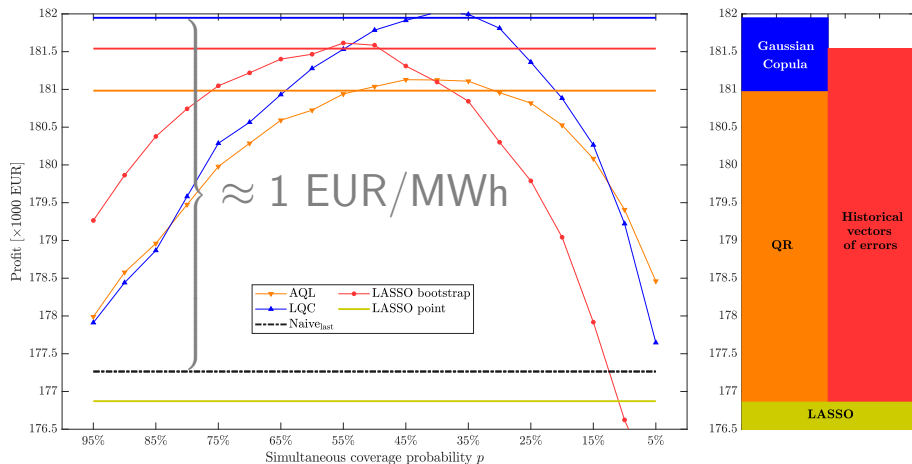
Prediction bands-based trading strategies

(Serafin, Marcjasz & Weron, 2021, WP)



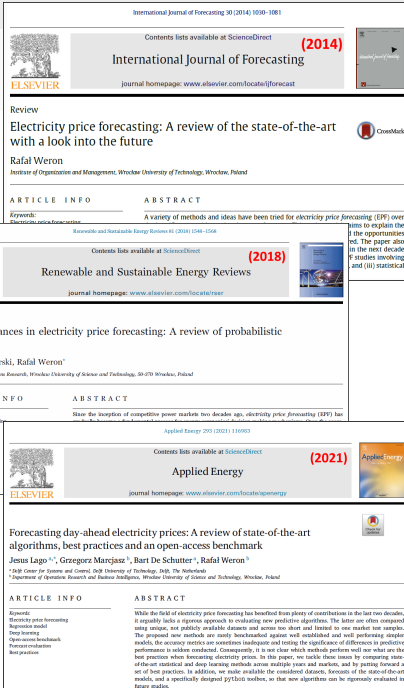
Profits: Selling 1 MW every hour for 200 days

(Serafin, Marcjasz & Weron, 2021, WP)



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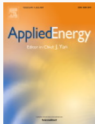
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Rafał Weron

Professor of Management Science (Energy Forecasting)

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J. Lago, G. Marcjasz, B. De Schutter, **R. Weron** (2021) *Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark*, Applied Energy 293, 116983 [Open Access](#) (doi: [10.1016/j.apenergy.2021.116983](https://doi.org/10.1016/j.apenergy.2021.116983))

- The **epftoolbox** including Python codes for the two benchmark models (LEAR, DNN) and datasets is available from *GitHub*



T. Hong, P. Pinson, Y. Wang, **R. Weron**, D. Yang, H. Zareipour (2020) *Energy forecasting: A review and outlook*, IEEE Open Access Journal of Power and Energy 7, 376-388 [Open Access](#) (Invited Paper; doi: [10.1109/OAJPE.2020.3029979](https://doi.org/10.1109/OAJPE.2020.3029979))

- IEEE Open Access Journal of Power and Energy* was formerly known as *IEEE Power and Energy Technology Systems Journal*