

Recent advances in electricity price forecasting: A 2023 perspective

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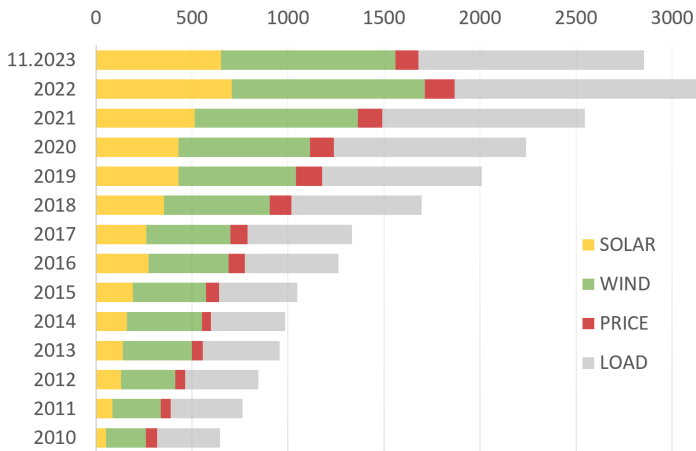
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<https://p.wz.pwr.edu.pl/~weron.rafal>



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

Energy (load, price, wind & solar) forecasting*

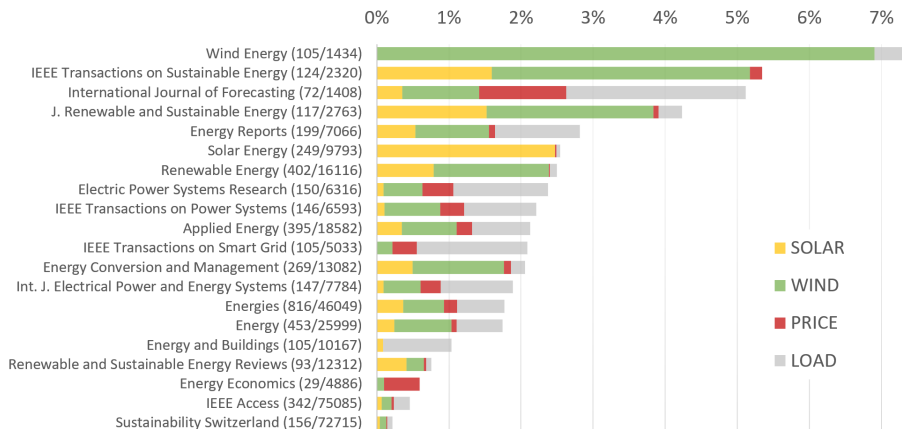
(Hong, Pinson, Wang, Weron, Yang & Zareipour, 2020, IEEE OAJPE)



* Number of Scopus indexed publications (29.11.2023 update)

Percentage of energy forecasting publications*

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

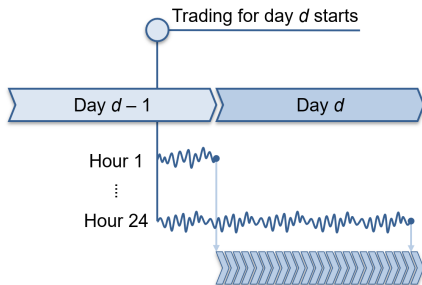
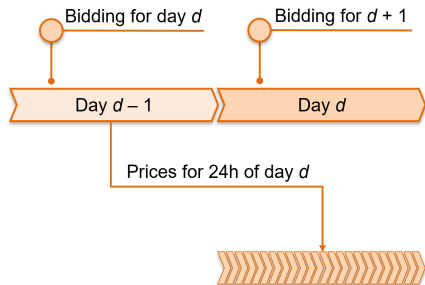


* Top 10 journals in each area (2010-11.2023); some are ranked top 10 across multiple areas

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

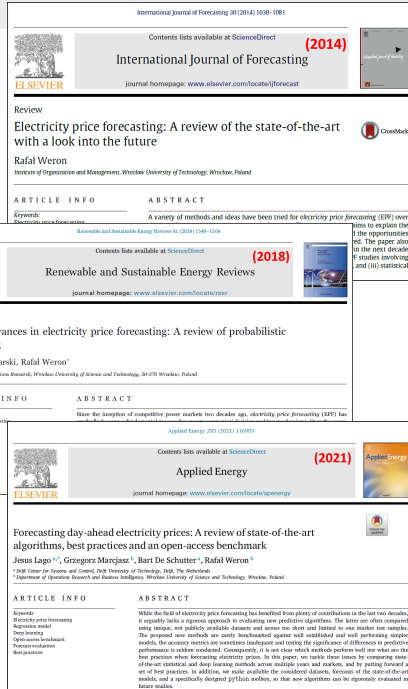
Day-ahead ($> 90\%$ of papers) vs. intraday markets

Auction vs. continuous trading



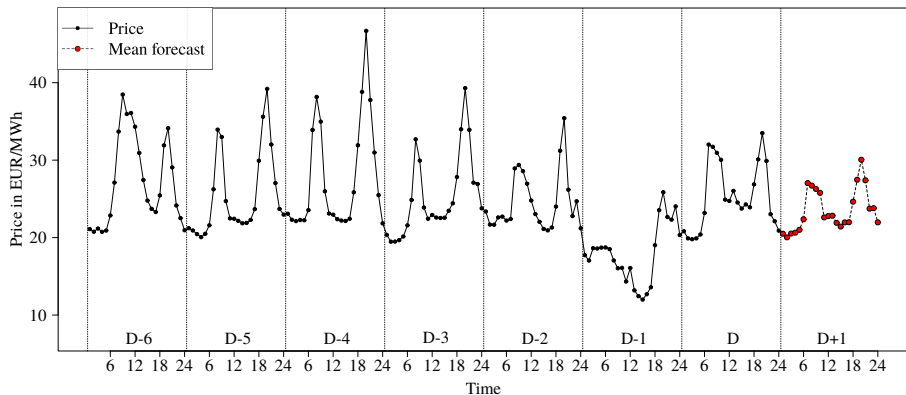
Agenda

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

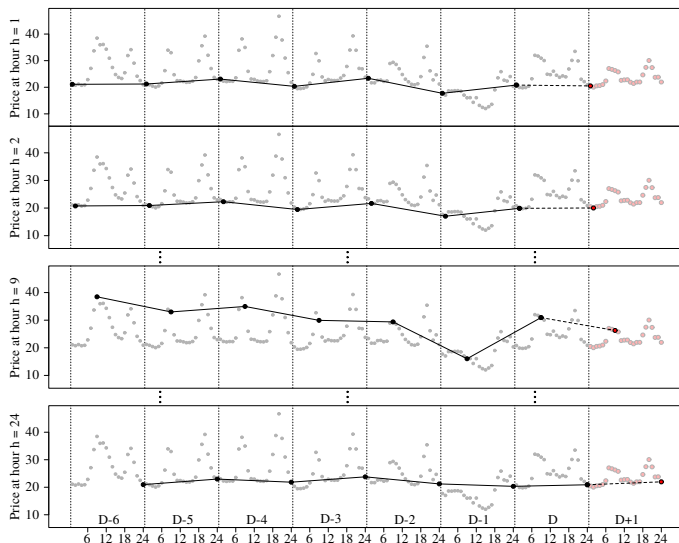


Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)

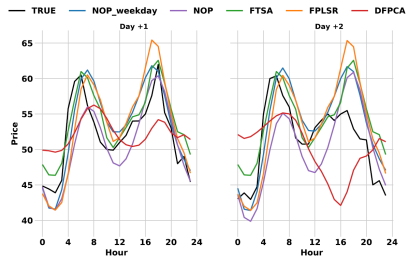
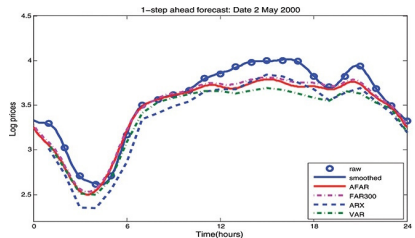
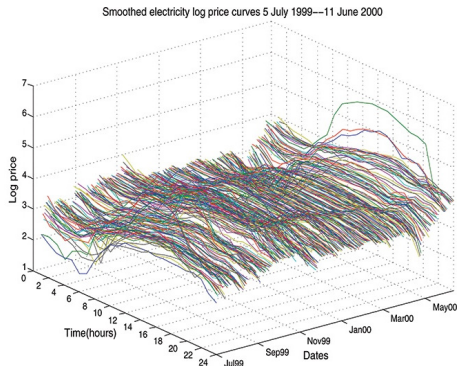


... multivariate ...



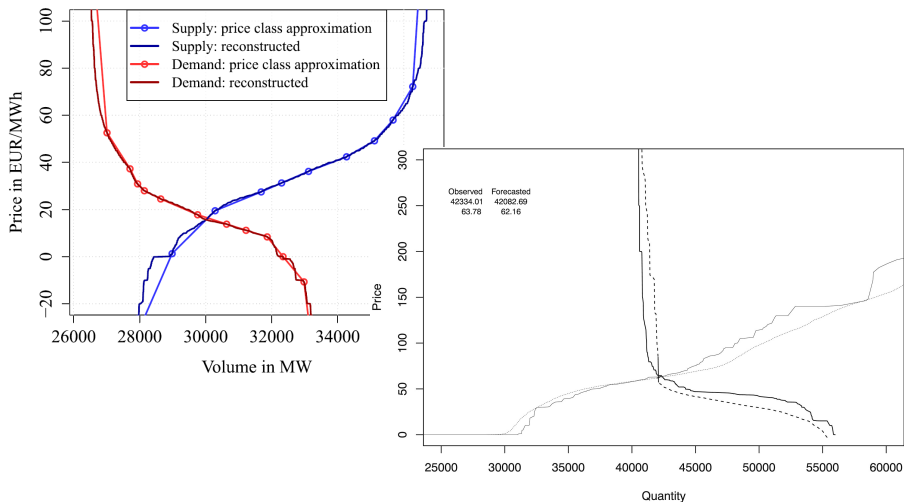
... functional (data analysis) ...

(Chen & Li, 2017, JBES; Chen et al., 2019, Ann.Appl.Stat; Wang & Cao, 2023, Environmetrics)



... or supply & demand curves?

(Ziel & Steinert, 2016, ENEECO; Shah & Lisi, 2020, J.Forecasting)



Which modeling framework?

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

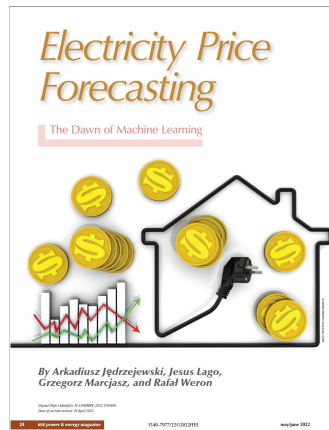
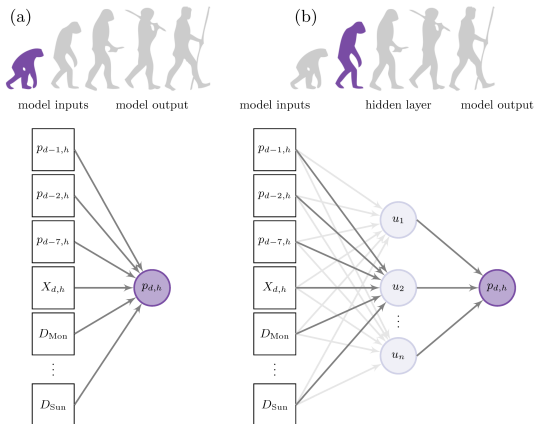
A simple autoregressive structure with exogenous variables (ARX):

$$\begin{aligned}
 p_{d,h} = & \underbrace{\beta_1 p_{d-1,h} + \beta_2 p_{d-2,h} + \beta_3 p_{d-7,h}}_{\text{autoregressive effects}} + \underbrace{\beta_4 X_{d,h}^{(1)} + \beta_5 X_{d,h}^{(2)}}_{\text{exogenous variables}} \\
 & + \underbrace{\beta_6 D_{Sat} + \beta_7 D_{Sun} + \beta_8 D_{Mon}}_{\text{weekday dummies}} + \varepsilon_{d,h},
 \end{aligned}$$

e.g., load (demand) and renewable generation day-ahead forecasts

Which modeling framework?

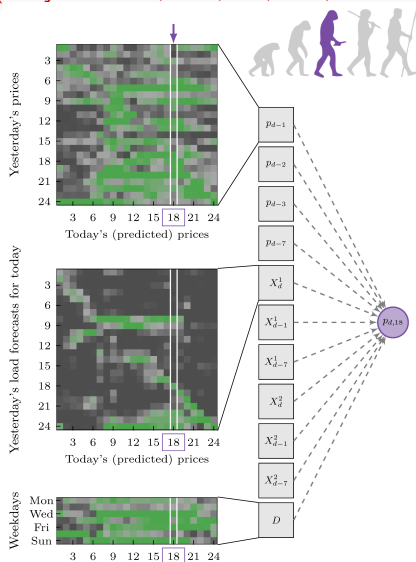
(Jędrzejewski, Lago, Marcjasz & Weron, 2022, IEEE-PEM)



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

LASSO-Estimated AR (LEAR)

(Uniejewski et al., 2016; Ziel, 2016; Ziel & Weron, 2018; Jędrzejewski et al., 2022)

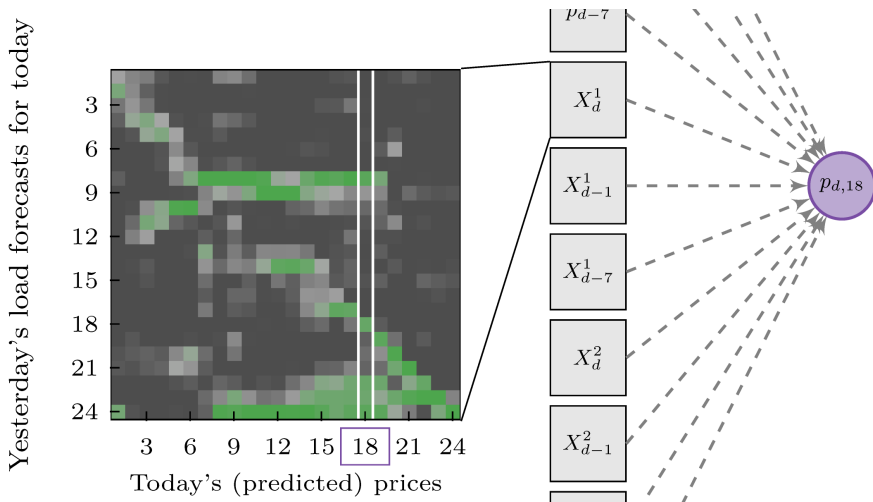


Minimize the residual sum of squares (**RSS**) + a **penalty**:

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

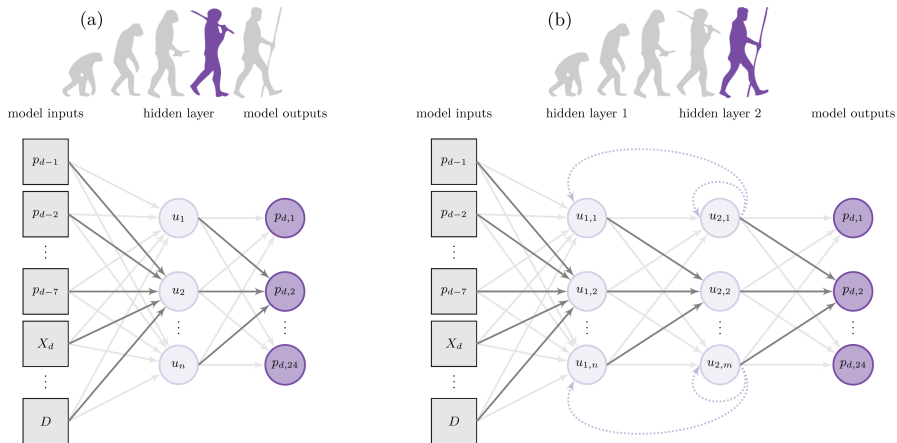
LASSO-Estimated AR (LEAR)

(Uniejewski et al., 2016; Ziel, 2016; Ziel & Weron, 2018; Jędrzejewski et al., 2022)



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

What about performance?

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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

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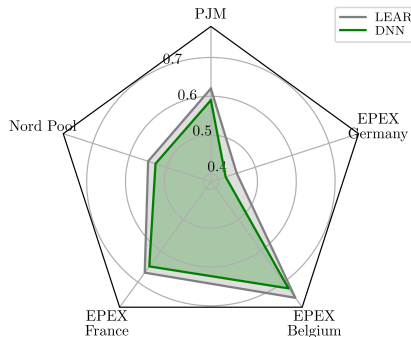
Keywords:

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 models. The proposed new methods are rarely benchmarked against existing models, the accuracy metrics are sometimes inadequate and test performance is seldom conducted. Consequently, it is not clear what best practices when forecasting electricity prices. In this paper, of-the-art statistical and deep learning methods across multiple sets of best practices. In addition, we make available the considered models, and a specifically designed python toolbox, so that new future studies.

rMAE (relative to a naive forecast)



epftoolbox: LEAR and DNN Python codes

(Lago et al., 2021, APEN)

The screenshot shows a web browser displaying the 'epftoolbox' website. The browser's address bar shows the URL 'https://epftoolbox.readthedocs.io/en/latest/modules/models.html'. The website has a blue header with the 'epftoolbox' logo and the word 'latest' below it. A search bar labeled 'Search docs' is present. A sidebar on the left contains a navigation menu with the following items: 'Getting started', 'Data management', 'Forecasting models' (which is expanded), 'The LEAR model', 'The DNN model', 'Model evaluation', 'Examples', and 'Citation'. The main content area is titled 'Forecasting models' and includes a link to 'Edit on GitHub'. The text describes the subpackage as providing an easy interface to two state-of-the-art forecasting models in the field of electricity price forecasting. It lists two bullet points: 'The LEAR model' and 'The DNN model'. The text further explains that for the LEAR model, the subpackage provides an interface for estimation, daily recalibration, and prediction, while for the DNN model, it provides an interface for estimation, hyperparameter optimization, daily recalibration, and prediction.

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Getting started
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☷ Forecasting models

The LEAR model
The DNN model
Model evaluation
Examples
Citation

Docs » Forecasting models [Edit on GitHub](#)

Forecasting models

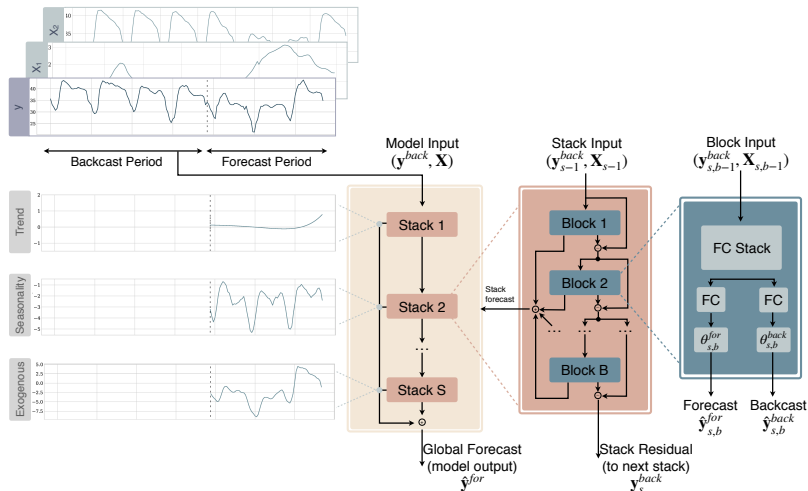
This subpackage provides an easy interface to two state-of-the-art forecasting models in the field of electricity price forecasting:

- [The LEAR model](#)
- [The DNN model](#)

For the [LEAR](#) model, the subpackage provides an interface to perform estimation, daily recalibration, and prediction. For [DNN](#) model, it provides an interface to perform estimation, hyperparameter optimization, daily recalibration, and prediction.

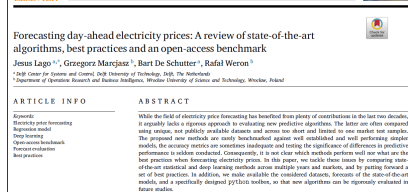
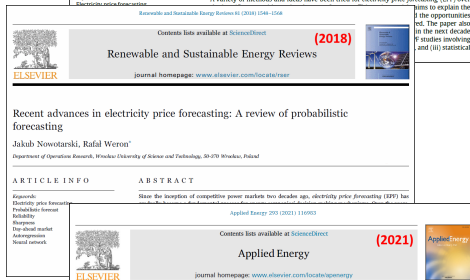
Interpretable NNs: NBEATSx

(Olivares, Challu, Marcjasz, Weron & Dubrawski, 2023, IJF)

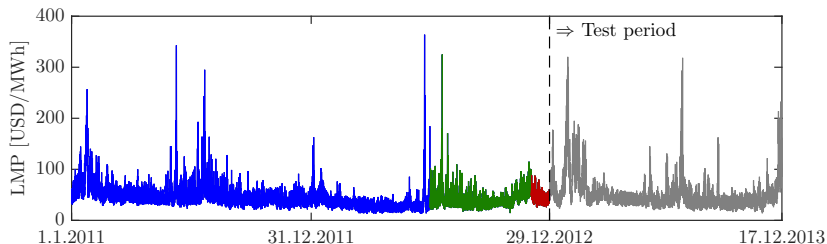


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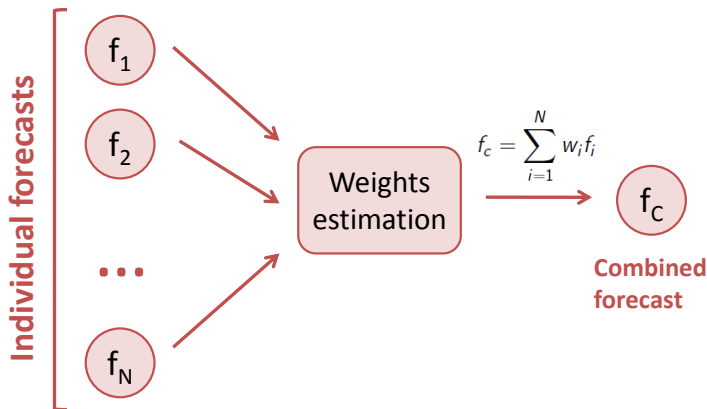


Searching for the optimal calibration window



- 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

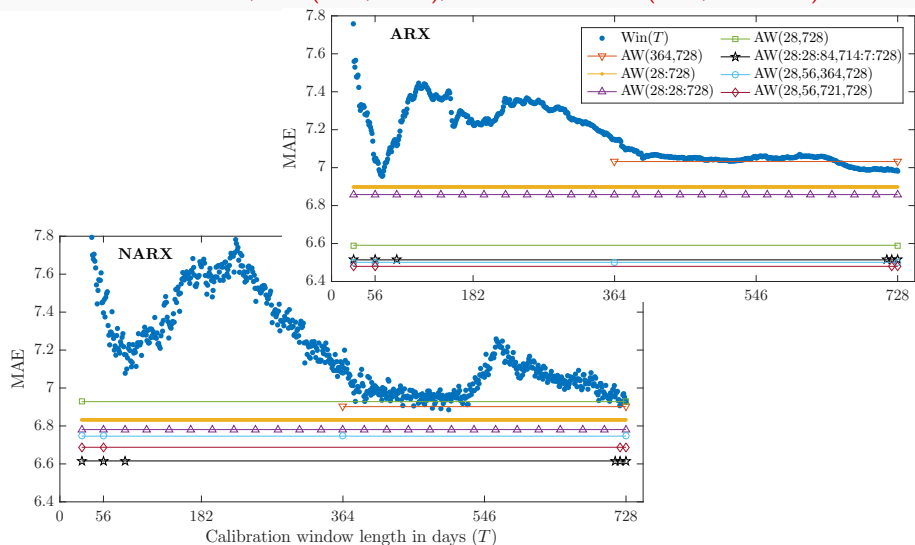
Point forecast averaging: The idea



- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger
- 'AI world': *committee machines*, *ensemble averaging*, *expert aggregation*

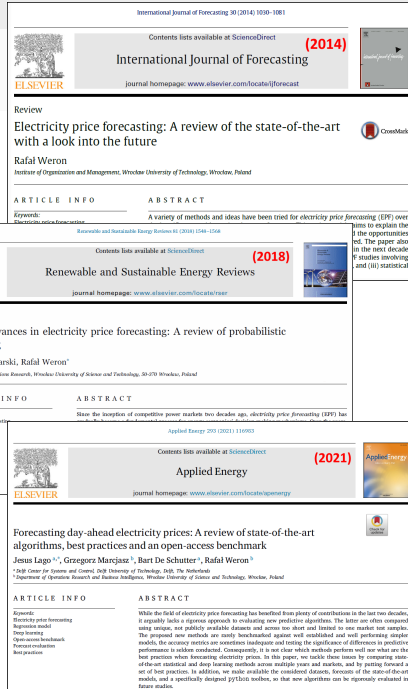
Averaging across calibration windows

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



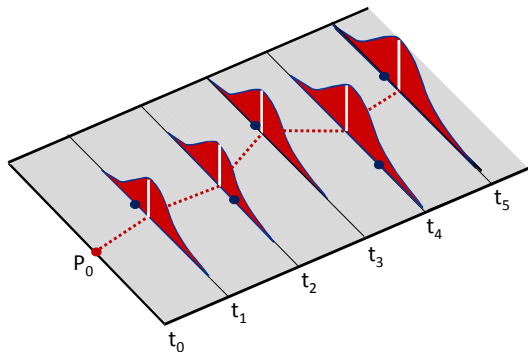
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Probabilistic (interval, density) forecasting

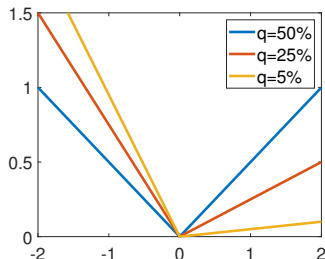
- We cannot observe the true underlying distribution
 $\Rightarrow$ we cannot compare the *predictive distribution* $\hat{F}_{Y_t}$ with the actual one F_{Y_t} ... only with past observations $Y_\tau, \tau < t$
- Gneiting et al.
(2007a, 2007b, 2014):
*'maximize **sharpness**
subject to **reliability**'*



Sharpness and the pinball score (or loss)

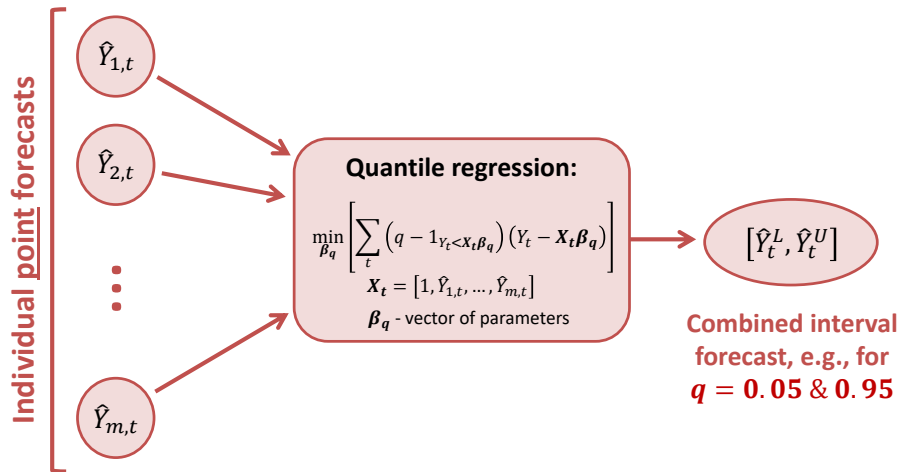
$$\mathbf{PS} \left(\hat{Y}_t^q, Y_t, q \right) = \begin{cases} (1 - q) \left(\hat{Y}_t^q - Y_t \right) & \text{for } Y_t < \hat{Y}_t^q \\ q \left(Y_t - \hat{Y}_t^q \right) & \text{for } Y_t \geq \hat{Y}_t^q \end{cases}$$

- $\hat{Y}_t^q$ is the forecast of the q -th quantile
- Y_t is the actual observation
- Also known as the **quantile score** or the **linlin/bilinear/newsboy loss**
- For an aggregate PS (**APS**) average:
 - across all t in the test period
 - across all quantiles $\rightarrow$ **CRPS**

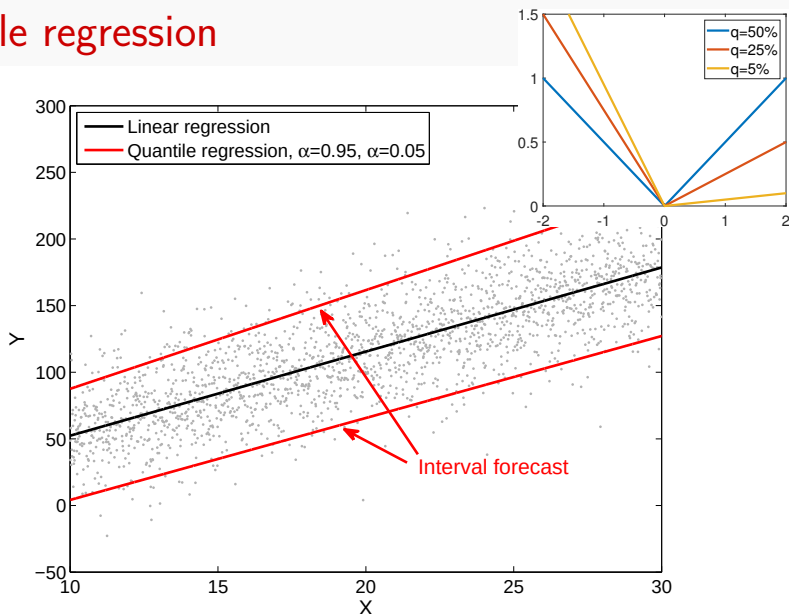


Quantile Regression Averaging: The idea

(Nowotarski & Weron, 2015, COST)

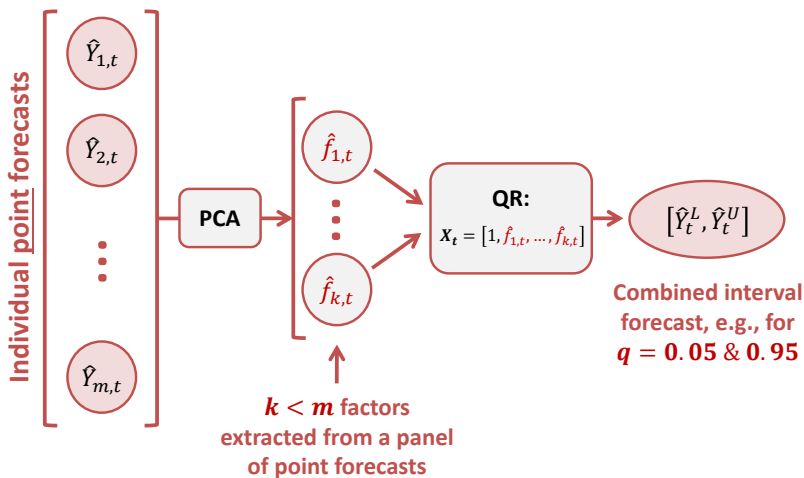


Quantile regression



FQRA: When the number of predictors is large

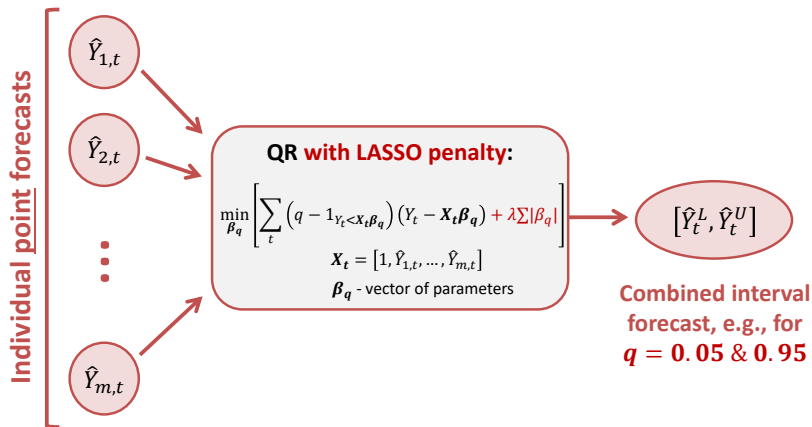
(Maciejowska, Nowotarski & Weron, 2016, IJF)



LQRA: When the number of predictors is large

(Uniejewski & Weron, 2021, ENEECO)

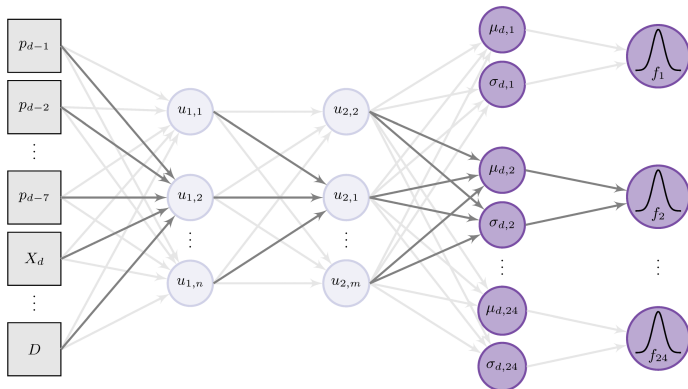
~ 5% improvement over QRA



Distributional Deep Neural Nets (DDNN)

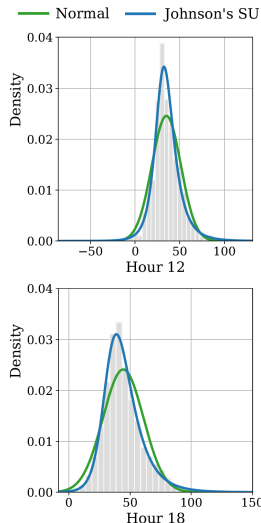
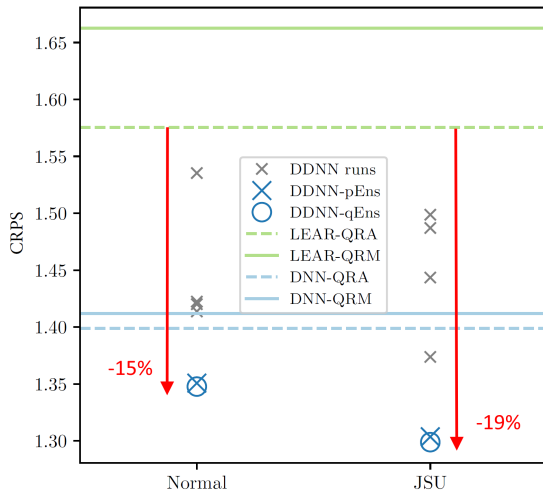
(Jędrzejewski et al., 2022, IEEE-PEM; Marcjasz, Narajewski, Weron & Ziel, 2023, ENEECO)

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



Perform surprisingly well ...

(Marcjasz, Narajewski, Weron & Ziel, 2023, ENEECO)



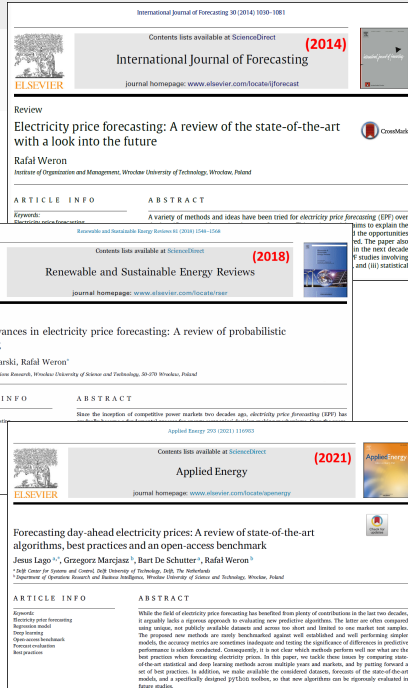
... also for point forecasts

(Marcjasz, Narajewski, Weron & Ziel, 2023, ENEECO)

	MAE	RMSE	CRPS
LEAR-Ens	4.372	6.375	-
naive	9.336	14.358	3.585
LEAR-QRA	4.161	6.676	1.575
LEAR-QRM	4.285	6.788	1.662
DNN-QRA	3.668	5.845	1.399
DNN-QRM	3.670	5.821	1.412
DDNN-N-pEns	3.663	5.962	1.351
DDNN-N-qEns	3.670	5.962	1.348
DDNN-JSU-pEns	3.542	6.146	1.304
DDNN-JSU-qEns	3.564	6.174	1.299

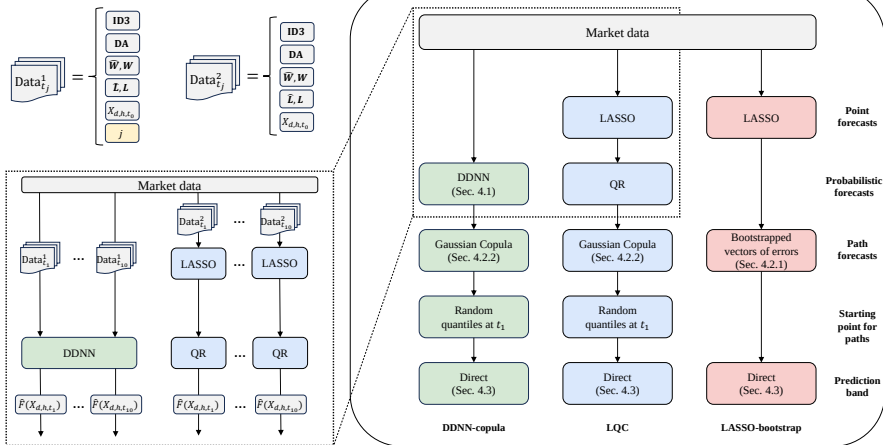
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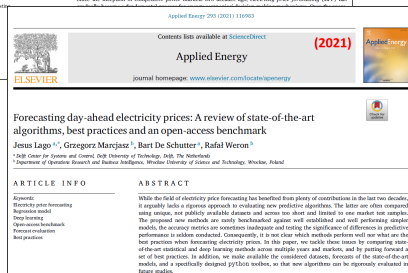
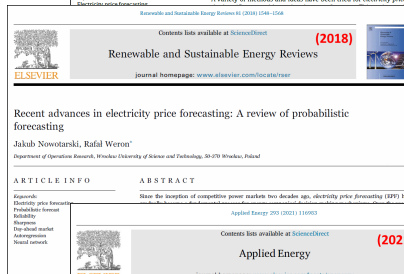
Path (trajectory, ensemble) forecasts

(Serafin, Marcjasz & Weron, 2022, ENEECO; 2023, WP)



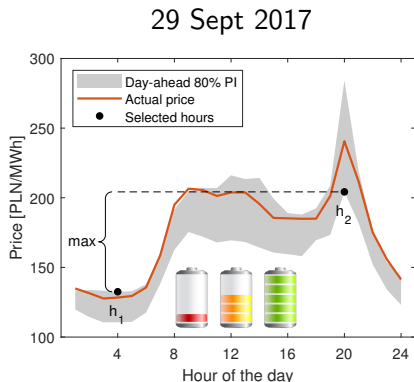
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Quantile-based trading strategies

(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

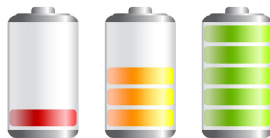
← With $\alpha = 10\%$ the spread is maximized for $\hat{P}_{d,4}^{90\%} = 133$ and $\hat{P}_{d,20}^{10\%} = 204$ PLN/MWh

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

Quantile-based trading strategies: Results

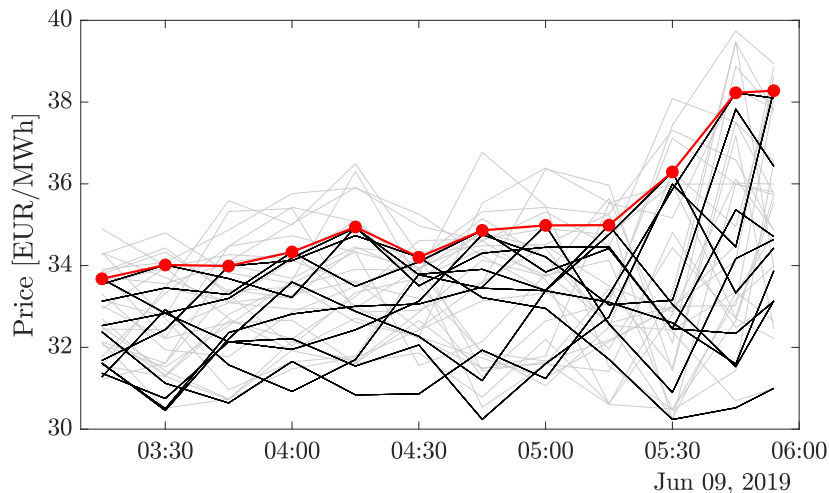
(Uniejewski & Weron, 2021, ENEECO)

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

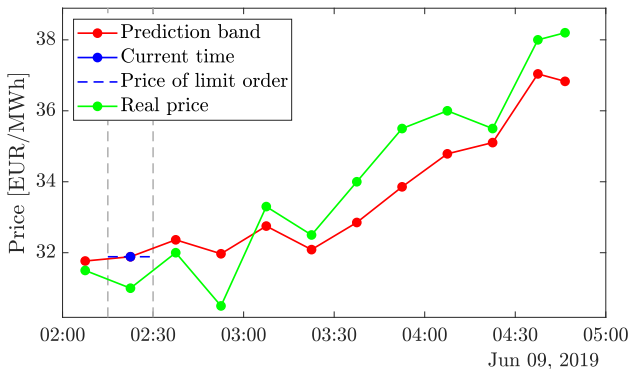
(Serafin, Marcjasz & Weron, 2022, ENEECO)



Prediction bands-based trading strategies

(Serafin, Marcjasz & Weron, 2022, ENEECO)

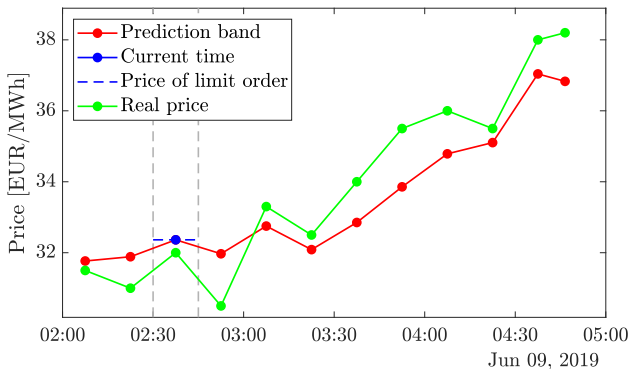
- The prediction band determines the price of the *limit order* which is placed in the market every 15 minutes



Prediction bands-based trading strategies

(Serafin, Marcjasz & Weron, 2022, ENEECO)

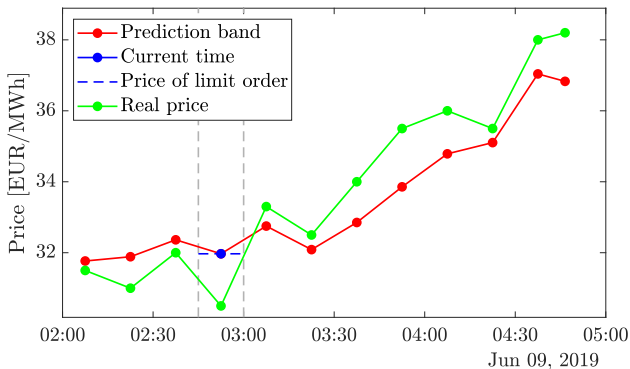
- If the order is not filled, the limit order is modified to match the next value of the prediction band



Prediction bands-based trading strategies

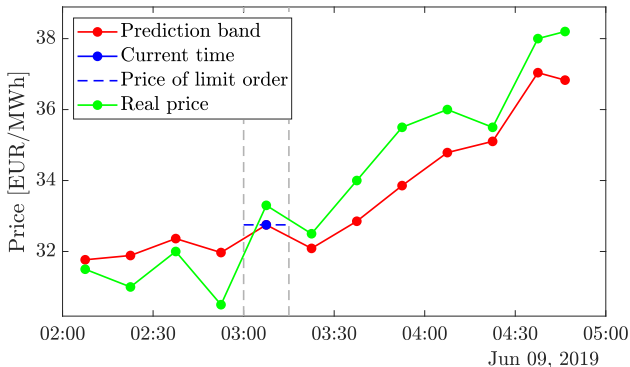
(Serafin, Marcjasz & Weron, 2022, ENEECO)

- If the order is not filled, the limit order is modified to match the next value of the prediction band ... again and again ...



Prediction bands-based trading strategies

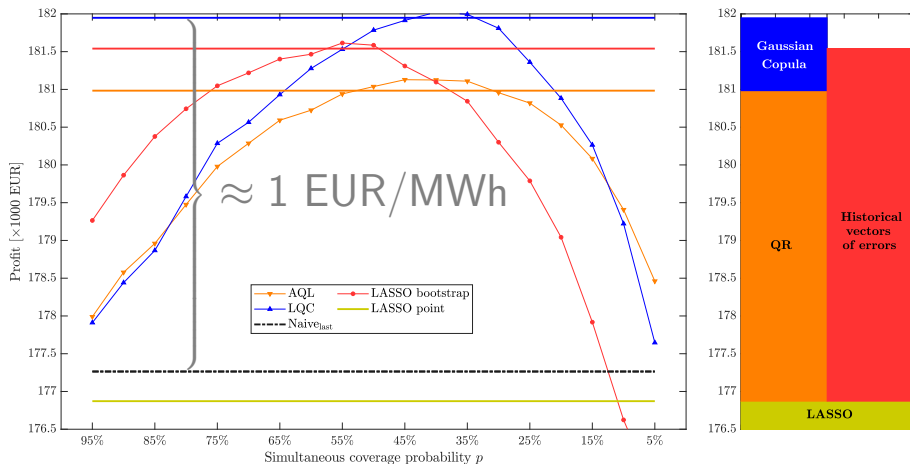
(Serafin, Marcjasz & Weron, 2022, ENEECO)



- If none of the orders was filled, the electricity is sold at the last price in the market

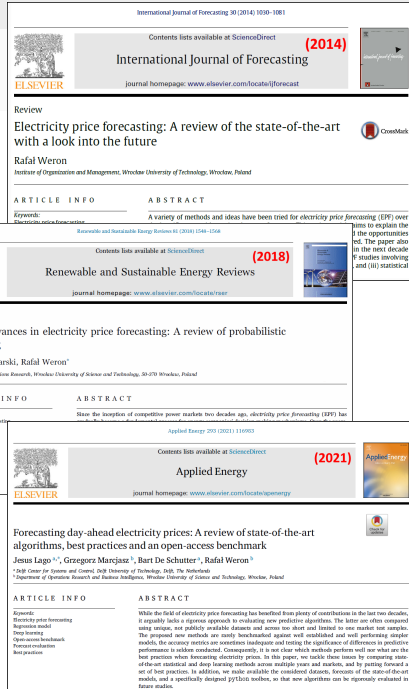
Profits: Selling 1 MWh every hour for 200 days

(Serafin, Marcjasz & Weron, 2022, ENEECO)



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Rafał Weron

Professor of Management Science (Energy Forecasting)

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Publications

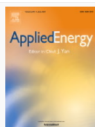
Projects

S3 Seminar

Conferences

Students

Monographs, reviews and edited volumes



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](#)



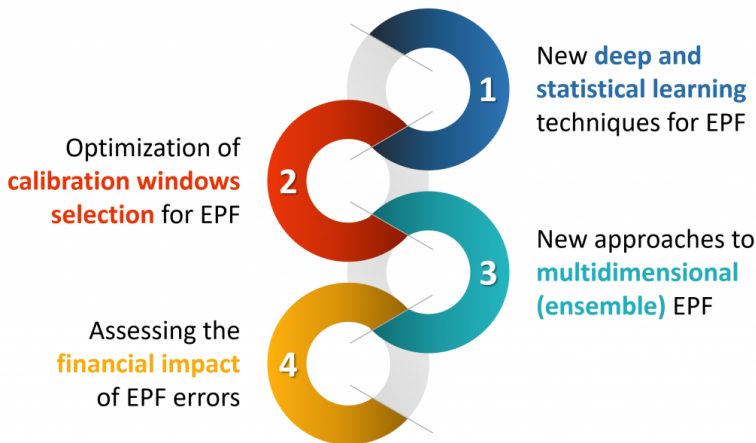
T. Hong, P. Pinson, Y. Wang, **R. Weron**, D. Yang, H. Zareipour (2020) *Energy forecasting: A review and outlook*, IEEE Open Access Journal of Power and Energy 7, 376-388 **Open Access** (Invited Paper; doi: [10.1109/OAJPE.2020.3029979](https://doi.org/10.1109/OAJPE.2020.3029979))

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

CrossFIT (2019-2024)

Crossing Frontiers in electricity price forecasting

(<https://kbo.pwr.edu.pl/en/research/research-projects/ncn-2018-30-a-hs4-00444>)



PRIORITY (2023-2026)

PRobabilistic mid- and long-term prlce fORecasting In electriciT Y markets

(<https://kbo.pwr.edu.pl/en/research/research-projects/dfg-ncn-2021-43-i-hs4-02578-2>)

