Recent advances in electricity price forecasting: A 2024 perspective

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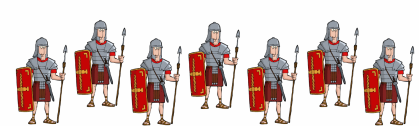
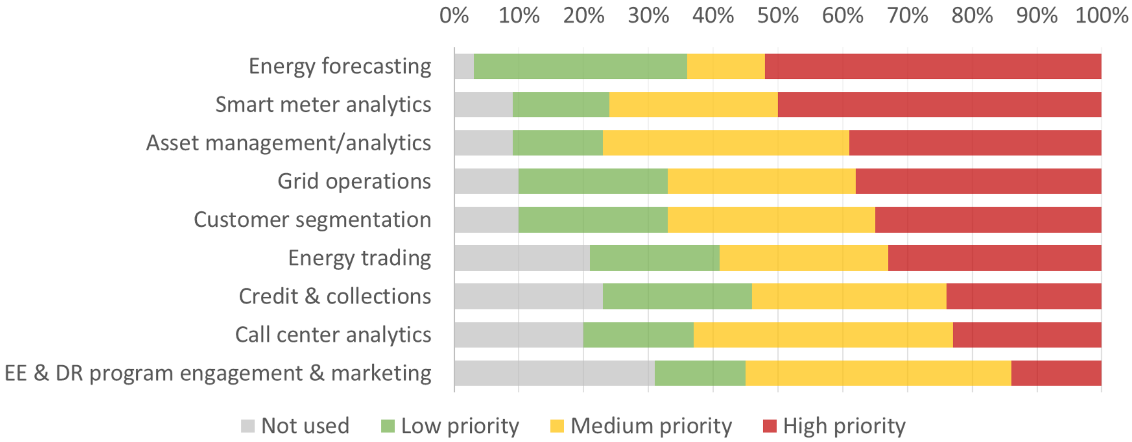


*Based on joint work with A.Lipiecki, K.Maciejowska, W.Nitka, T.Serafin, B.Uniejewski (Wrocław Tech), C.Challu, K.Olivares (Carnegie Mellon), A.Jędrzejewski (U.Cergy-Pontoise), F.Ziel (U.Duisburg-Essen), K.Hubicka (UBS), C.Kath (RWE), J.Lago (Amazon), G.Marcjasz (Alpiq), M.Narajewski (Statkraft), J.Nasiadka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

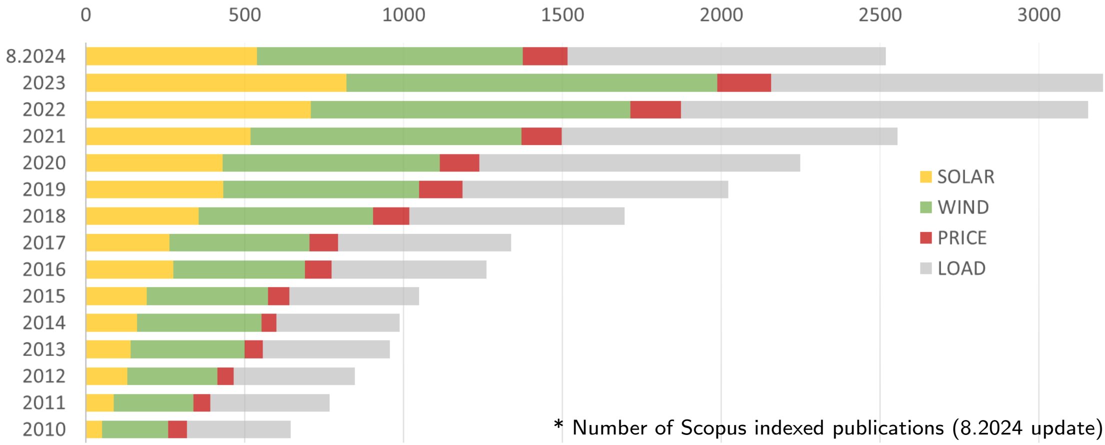
Energy forecasting is a top priority for utilities

(SAS, 2017, White Paper; responses from 136 utilities from 24 countries)



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

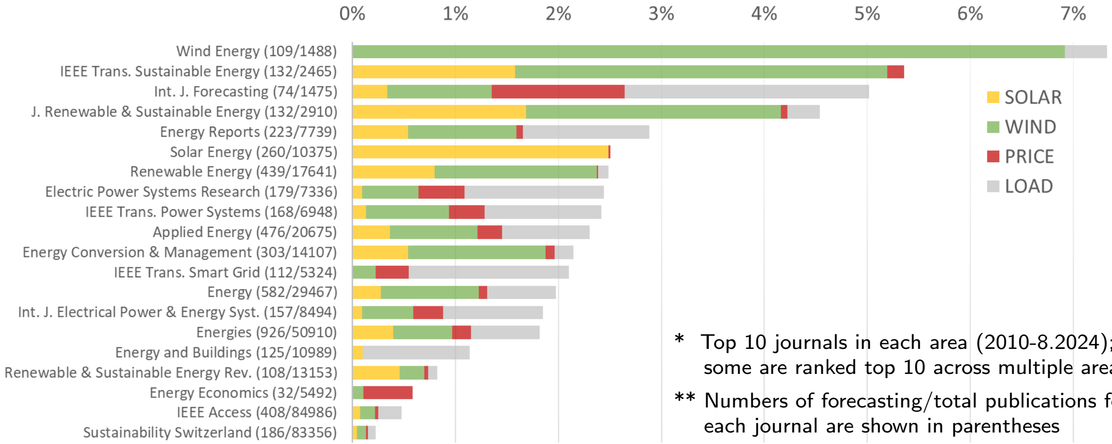
(Hong, Pinson, Wang, Weron, Yang & Zareipour, 2020, IEEE OAJPE)



* Number of Scopus indexed publications (8.2024 update)

Percentage of energy forecasting publications*

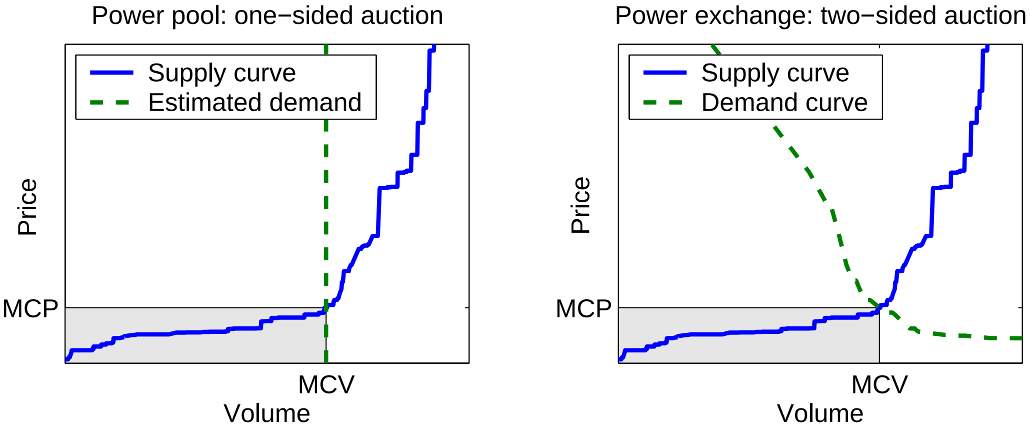
(Hong, Pinson, Wang, Weron, Yang & Zareipour, 2020, IEEE OAJPE)



* Top 10 journals in each area (2010-8.2024); some are ranked top 10 across multiple areas

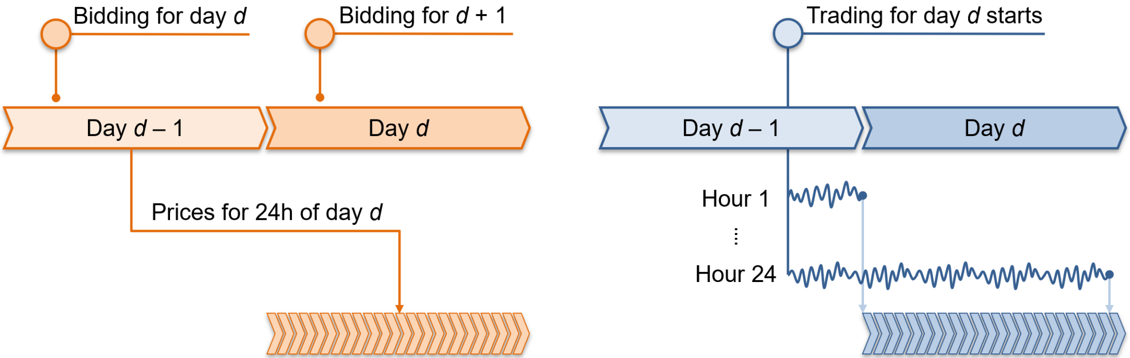
** Numbers of forecasting/total publications for each journal are shown in parentheses

Power pool vs. power exchange



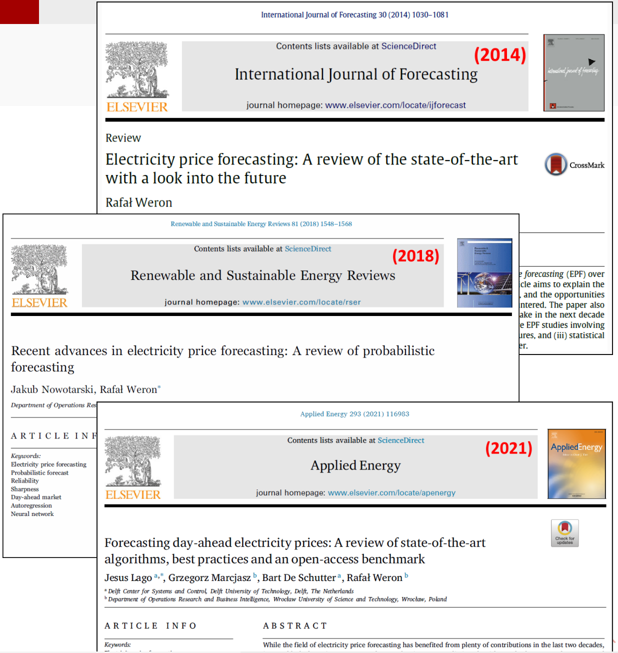
Day-ahead (> 90% of papers) vs. intraday markets

Auction vs. continuous trading



Agenda

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



International Journal of Forecasting 30 (2014) 1030–1081

Contents lists available at ScienceDirect

(2014)

International Journal of Forecasting

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

Review

Electricity price forecasting: A review of the state-of-the-art with a look into the future

Rafał Weron

… forecasting (EPF) over … cle aims to explain the …, and the opportunities … ntered. The paper also … ake in the next decade … e EPF studies involving … ures, and (iii) statistical … er.

Renewable and Sustainable Energy Reviews 81 (2018) 1548–1568

Contents lists available at ScienceDirect

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Jakub Nowotarski, Rafał Weron*

Department of Operations Res…

ARTICLE INF…

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

Applied Energy 293 (2021) 116983

Contents lists available at ScienceDirect

(2021)

Applied Energy

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

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]

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ARTICLE INFO

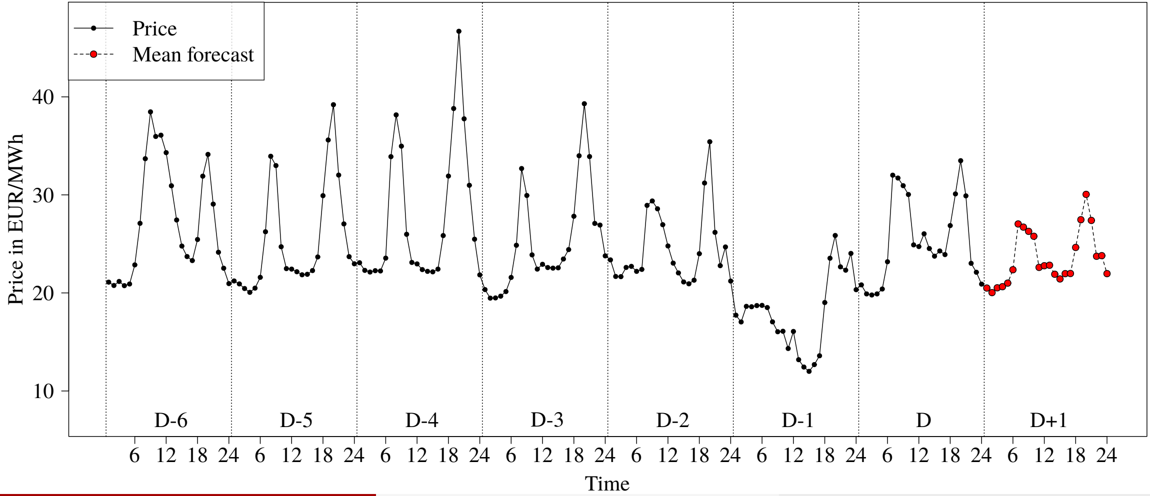
Keywords:

ABSTRACT

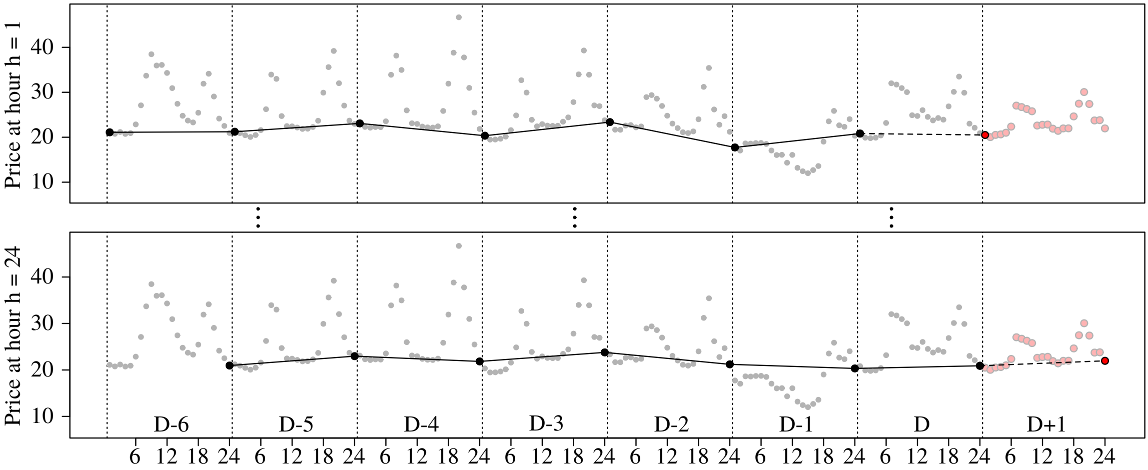
While the field of electricity price forecasting has benefited from plenty of contributions in the last two decades,

Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)

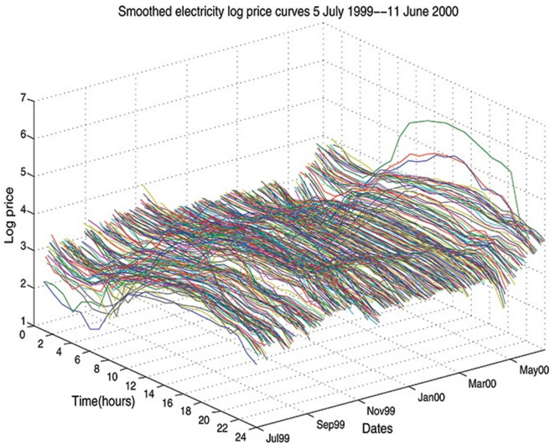


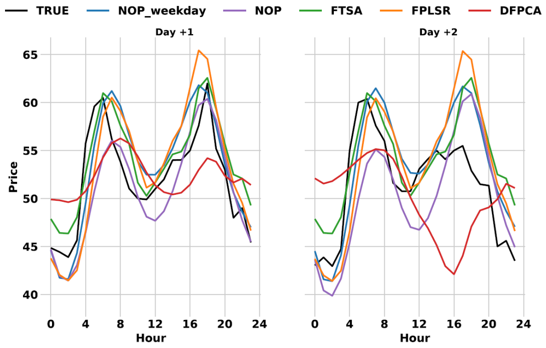
... multivariate ...



... functional (data analysis) ...

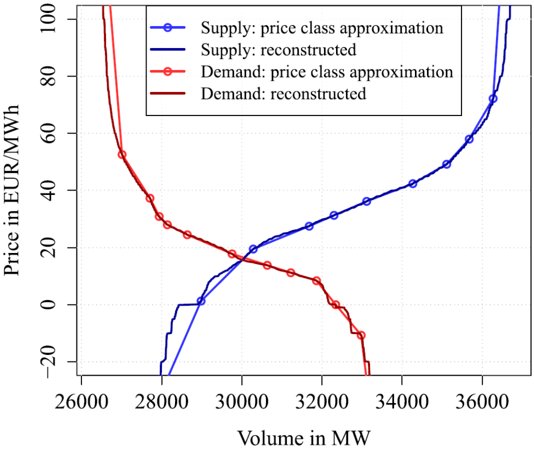
(Chen & Li, 2017, JBES; Chen et al., 2019, Ann.Appl.Stat; Wang & Cao, 2023, Environmetrics)

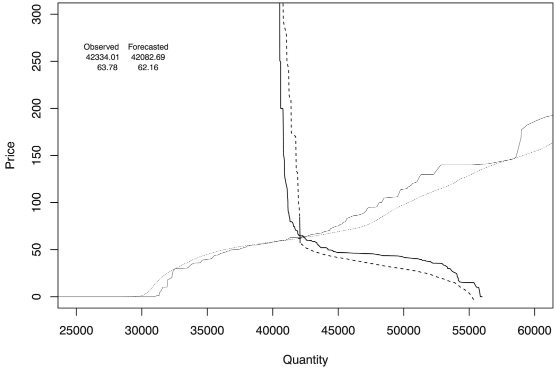




... or supply & demand curves?

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





Which modeling framework?

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

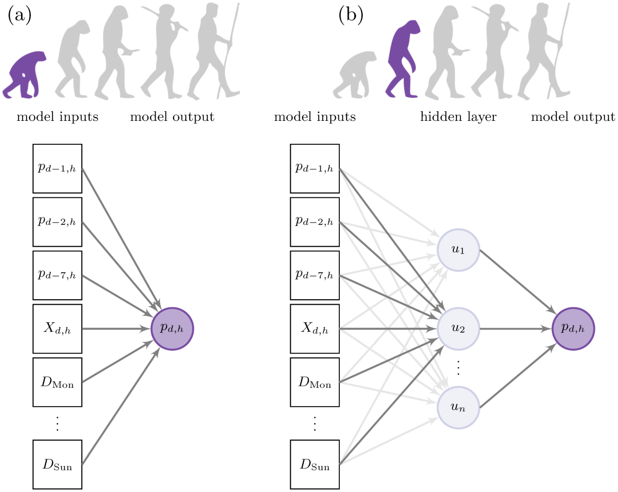
A simple autoregressive structure with exogenous variables (ARX):

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

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

Which modeling framework?

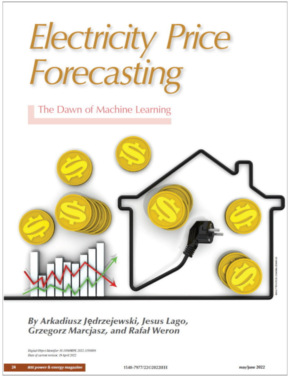
(Jędrzejewski, Lago, Marcjasz & Weron, 2022, IEEE-PEM)



Early EPF models:

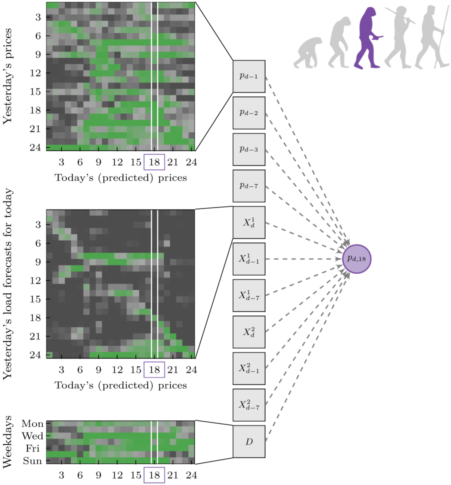
(a) linear regression

(b) single-output shallow neural network



LASSO-Estimated AR (LEAR)

(Uniejewski et al., 2016; Ziel, 2016; Ziel & Weron, 2018; Jędrzejewski et al., 2022; Uniejewski, 2024)



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

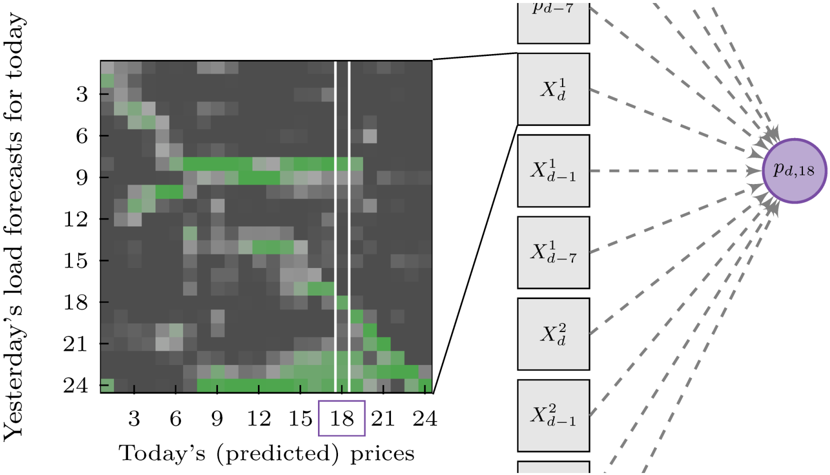
$$\hat{\beta} = \underset{\beta_j}{\text{argmin}} \left\{ \text{RSS} + \lambda \sum_{j=1}^{n} |\beta_j| \right\}$$

Note: Whole 24-hourly vectors are inputs, not only values for the target hour $h = 18$

Uniejewski (2024, ORD) compares 10 penalties and finds that only Elastic Net and LQ consistently outperform LASSO

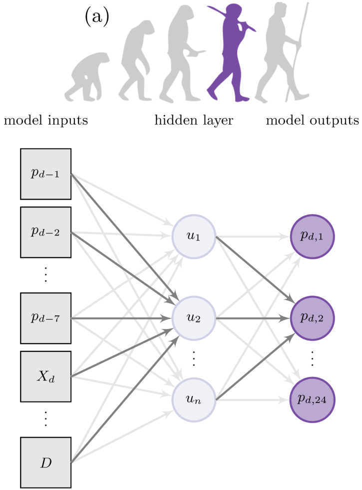
LASSO-Estimated AR (LEAR)

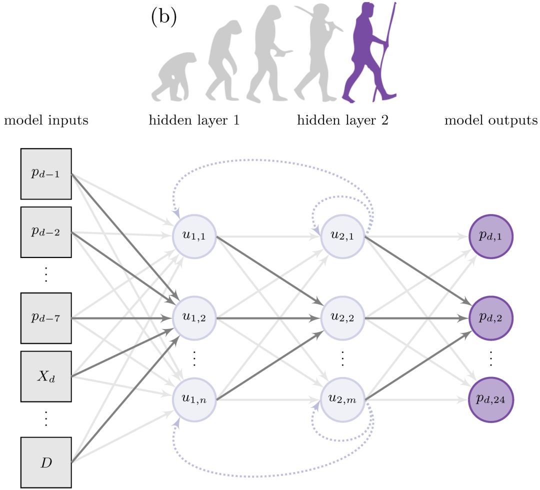
(Uniejewski et al., 2016; Ziel, 2016; Ziel & Weron, 2018; Jędrzejewski et al., 2022; Uniejewski, 2024)



Multi-output shallow and deep neural networks (DNNs)

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





What about performance?

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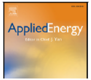
(2021)

Applied Energy

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



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]

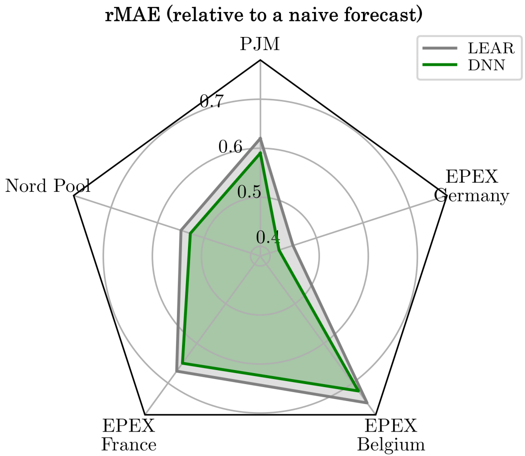
[a] Delft Center for Systems and Control, Delft University of Technology, Delft, The Netherlands
[b] Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology, Wrocław, Poland

ARTICLE INFO

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

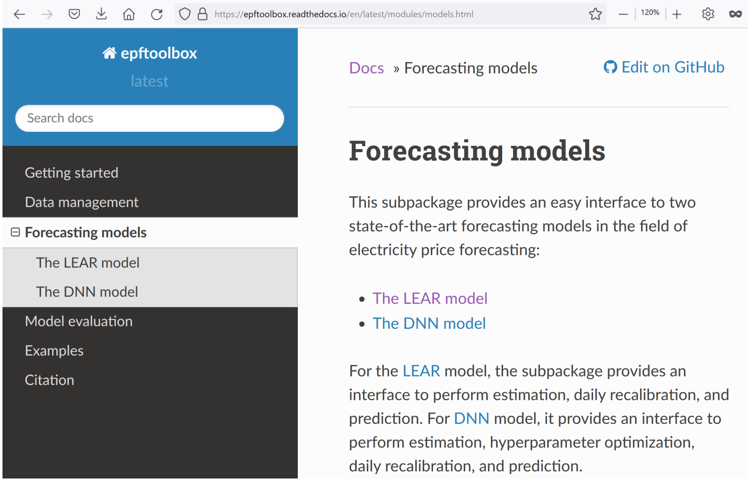
ABSTRACT

While the field of electricity price forecasting has benefited from plenty of c
it arguably lacks a rigorous approach to evaluating new predictive algorit
using unique, not publicly available datasets and across too short and l
The proposed new methods are rarely benchmarked against well establ
models, the accuracy metrics are sometimes inadequate and testing the sig
performance is seldom conducted. Consequently, it is not clear which met
best practices when forecasting electricity prices. In this paper, we tack
of-the-art statistical and deep learning methods across multiple years and
set of best practices. In addition, we make available the considered datas
models, and a specifically designed python toolbox, so that new algorit
future studies.



epftoolbox: LEAR and DNN Python codes

(Lago et al., 2021, APEN)


https://epftoolbox.readthedocs.io/en/latest/modules/models.html

epftoolbox
latest

Search docs

- Getting started
- Data management
- 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:

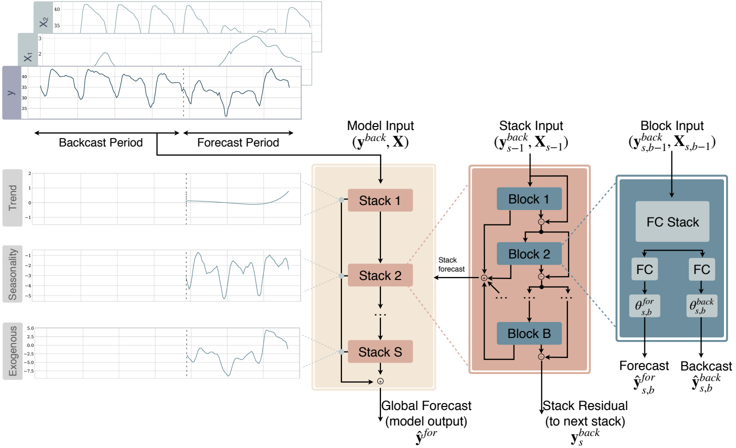
- The LEAR model
- The DNN model

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.

Experiment yourself:

Interpretable NNs: NBEATSx

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



Experiment yourself:

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ABSTRACT

While the field of electricity price forecasting has benefited from plenty of contributions in the last two decades,

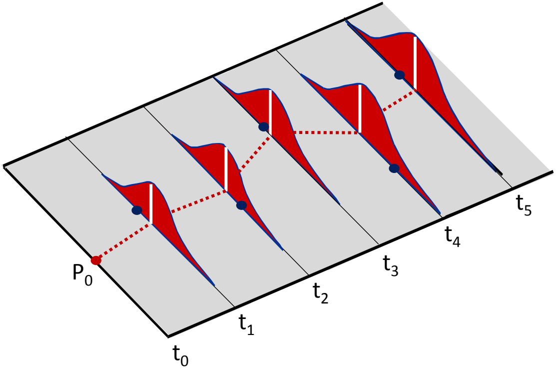
Probabilistic (interval, density) forecasting

- 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***'

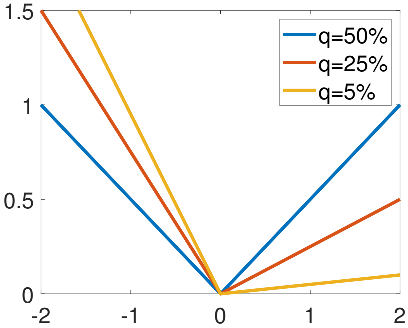
- An $x\%$ prediction interval (PI)
  is **reliable** if it includes $x\%$
  of the observations



Sharpness and the pinball score (or loss)

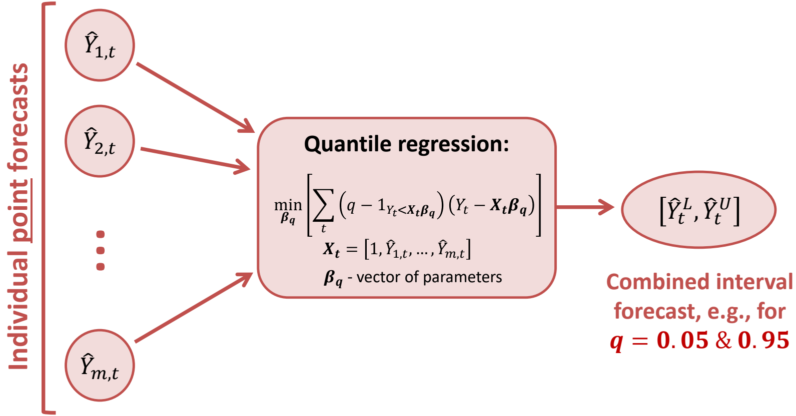
$$\mathbf{PS}\left(\hat{Y}_t^q, Y_t, q\right) = \begin{cases} (1-q)\left(\hat{Y}_t^q - Y_t\right) & \text{for } Y_t < \hat{Y}_t^q \\ q\left(Y_t - \hat{Y}_t^q\right) & \text{for } Y_t \geqslant \hat{Y}_t^q \end{cases}$$

- $\hat{Y}_t^q$ 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 (QRA): The idea

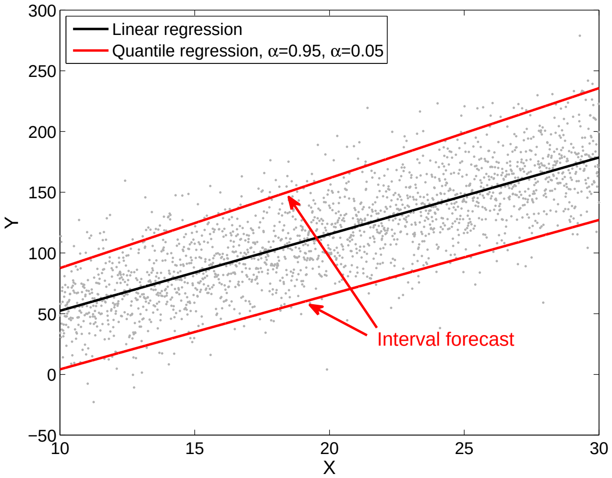
(Nowotarski & Weron, 2015, COST)

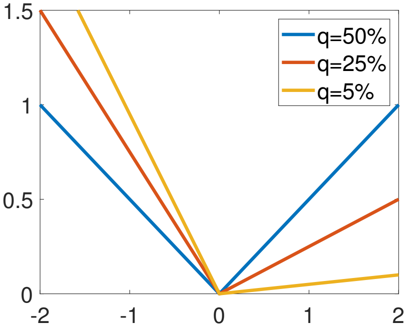


Averaging dates back to the 1960s and the works of Bates, Crane, Crotty & Granger

'AI world': *committee machines*, *ensemble averaging*, *expert aggregation*

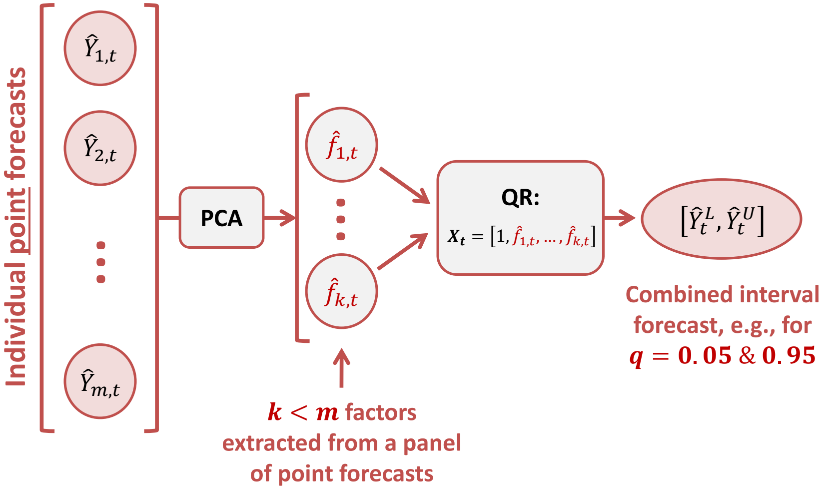
Quantile regression





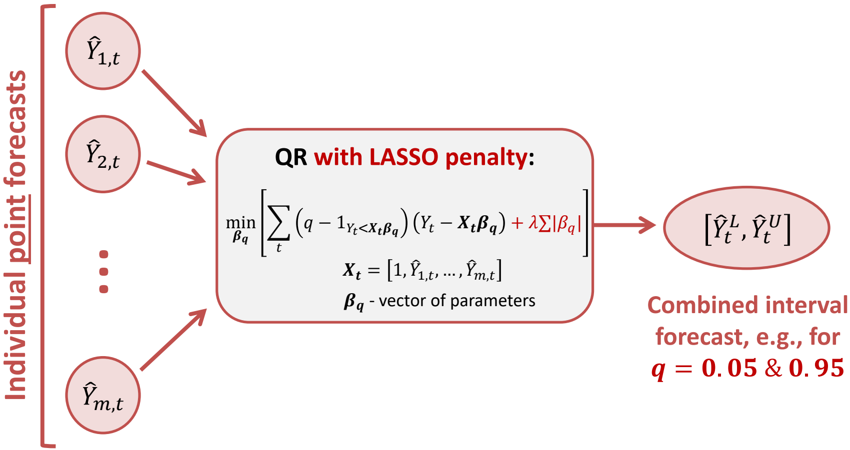
Factor QRA (FQRA): When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



LASSO QRA (LQRA): When the number of predictors is large

(Uniejewski & Weron, 2021, ENEECO) $\sim$ 5% improvement over QRA



QR(A) is not the only postprocessing approach

(Nowotarski & Weron, 2018, RSER; Lipiecki & Weron, 2024, WP)

- $N(0, \hat{\sigma}(\varepsilon_{d,h}))$-distributed innovations, where $\varepsilon_{d,h}$ are point prediction errors
- Historical simulation, i.e., empirical CDF of $\varepsilon_{d,h}$
- Conformal Prediction (CP), i.e., empirical CDF of $|\varepsilon_{d,h}|$
  - Proposed by Gammerman et al. (1998, Conf), Shafer & Vovk (2008, JMLR), and by Kath & Ziel (2021, IJF) for EPF
- Isotonic Distributional Regression (IDR) – a non-parametric technique for the estimation of conditional distributions under order restrictions
  - Proposed by Henzi, Ziegel & Gneiting (2021, JRSSB) for weather forecasting, and by Lipiecki, Uniejewski & Weron (2024, ENEECO) for EPF

Julia package for postprocessing point predictions

(Lipiecki & Weron, 2024, WP + GitHub)

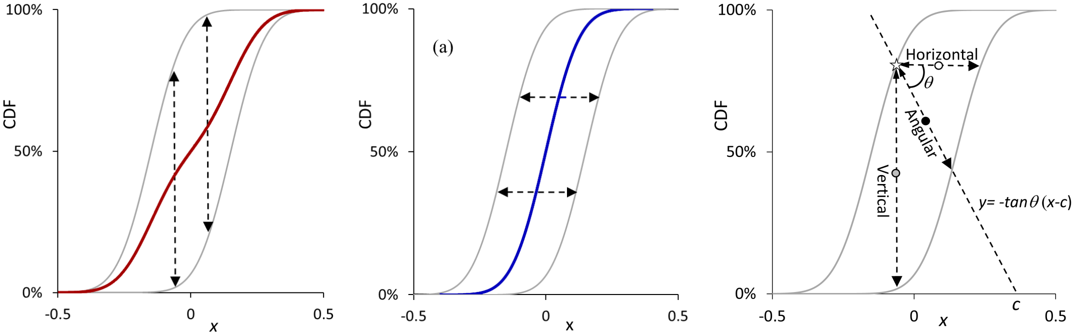
Offers implementations of CP, IDR, QR(A) and N(0,$\hat{\sigma}(\varepsilon_{d,h})$), and their combinations

Experiment yourself:

Combining probabilistic forecasts is tricky ...

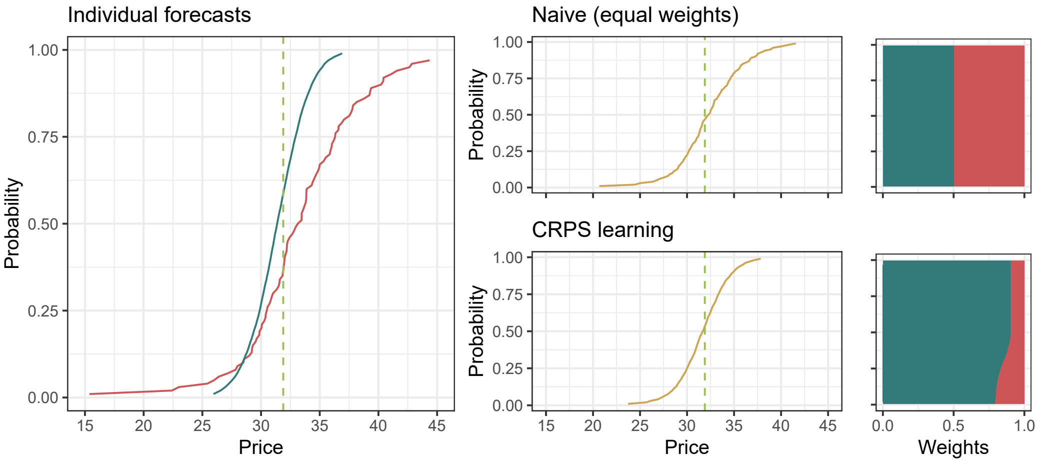
(Lichtendahl et al., 2013, Mgnt Sci; Uniejewski et al., 2019, ENEECO; Taylor & Meng, 2023, arXiv)

Vertical (over probabilities), **horizontal** (quantiles → sharper CDF) ... or at any angle



… can use unequal weights (here: CRPS learning) …

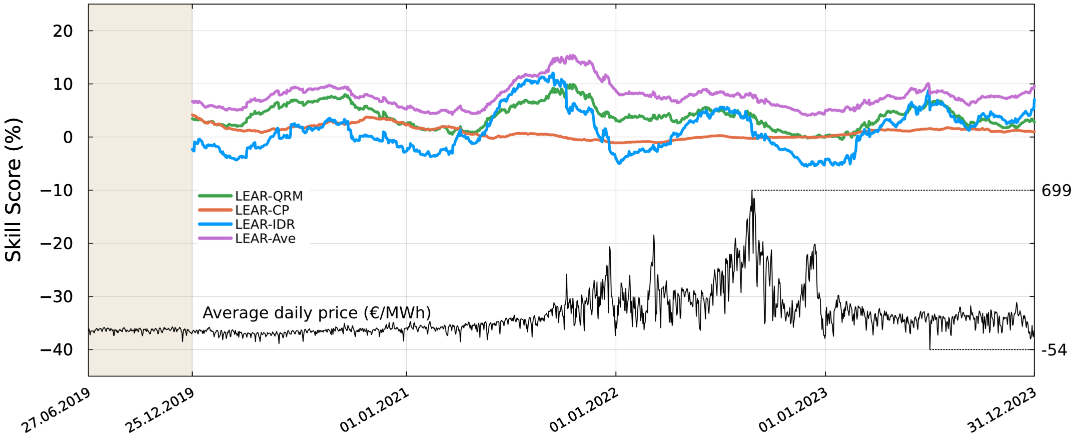
(Berrisch & Ziel, 2023, JEconometrics; Nitka & Weron, 2023, ORD)



... but can be beneficial

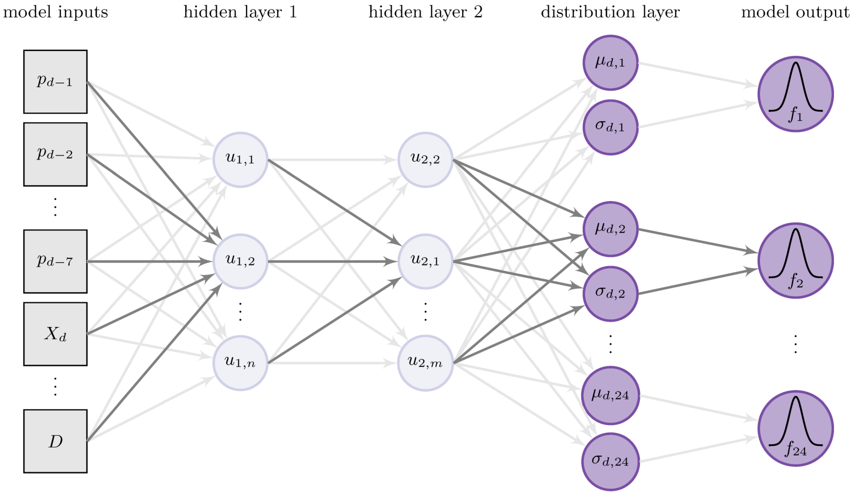
(Lipiecki, Uniejewski & Weron, 2024, ENEECO; illustrated here using EPEX-DE data)

Skill score: % difference wrt the CRPS of $N(0,\hat{\sigma}(\varepsilon_{d,h}))$ innovations; $\varepsilon_{d,h}$ – prediction errors of the LEAR model



Distributional Deep Neural Nets (DDNN)

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



DDNNs can perform very well ...

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

Energy Economics 125 (2023) 106843

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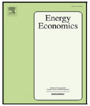


Check for updates

Distributional neural networks for electricity price forecasting

Grzegorz Marcjasz [a,*], Michał Narajewski [b], Rafał Weron [a], Florian Ziel [b]

[a] *Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology, 50-370 Wrocław, Poland*
[b] *House of Energy Markets and Finance, University of Duisburg–Essen, 45141 Essen, Germany*

A R T I C L E   I N F O

JEL classification:
C44
C45
C46
C22
C53
Q47

Keywords:
Distributional neural network
Probabilistic forecasting

A B S T R A C T

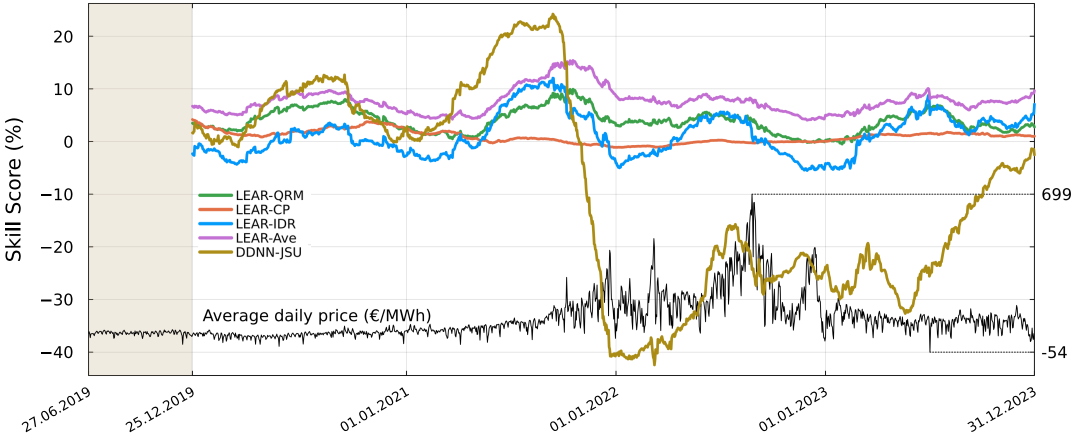
We present a novel approach to probabilistic electricity price forecasting which utilizes distributional neural networks. The model structure is based on a deep neural network containing a so-called probability layer, i.e., the outputs of the network are parameters of the normal or Johnson's SU distribution. To validate our approach, we conduct a comprehensive forecasting study complemented by a realistic trading simulation with day-ahead electricity prices in the German market. The proposed distributional deep neural network outperforms state-of-the-art benchmarks by over 7% in terms of the continuous ranked probability score and by 8% in terms of the per-transaction profits. The obtained results not only emphasize the importance of higher moments when modeling volatile electricity prices, but also – given that probabilistic forecasting is the essence of risk management – provide important implications for managing portfolios in the power sector.

Experiment yourself:

... but can fail miserably during volatile periods

(Lipiecki, Uniejewski & Weron, 2024, ENEECO; illustrated here using EPEX-DE data)

Skill score: % difference wrt the CRPS of $N(0,\hat{\sigma}(\varepsilon_{d,h}))$ innovations; $\varepsilon_{d,h}$ – prediction errors of the LEAR model



Agenda

1. Intro
2. Model evolution
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   - Going deep
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   - Probabilistic
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International Journal of Forecasting 30 (2014) 1030–1081

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Department of Operations Res...

ARTICLE INF...

Keywords:
Electricity price forecasting
Probabilistic forecast
Reliability
Sharpness
Day-ahead market
Autoregression
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Applied Energy 293 (2021) 116983

Contents lists available at ScienceDirect

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

(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

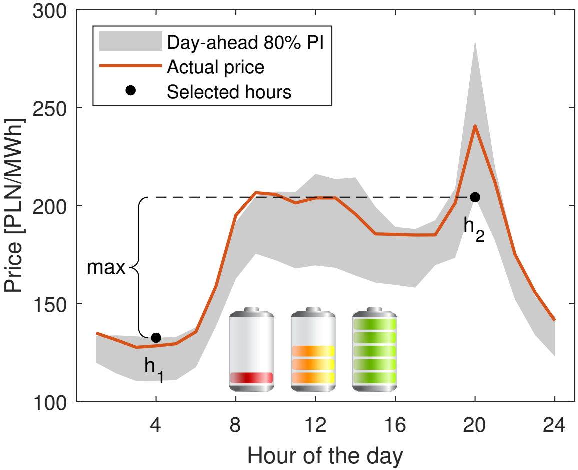
Keywords:

ABSTRACT

While the field of electricity price forecasting has benefited from plenty of contributions in the last two decades,

Quantile-based trading strategies

(Uniejewski & Weron, 2021, ENEECO)



Simultaneously bid day-ahead:

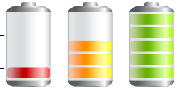
- buy 1 MW for $\hat{P}^{1-\alpha}_{d,h_1}$ at hour h_1
- sell 0.8 MW at $\hat{P}^{\alpha}_{d,h_2}$ at hour h_2

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

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

Are quantile-based trading strategies more profitable?

(Uniejewski & Weron, 2021, ENEECO)



Strategy			Profit		
Naive (4am–12pm)			33 065.29		
Point forecasts-based			33 722.39		
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

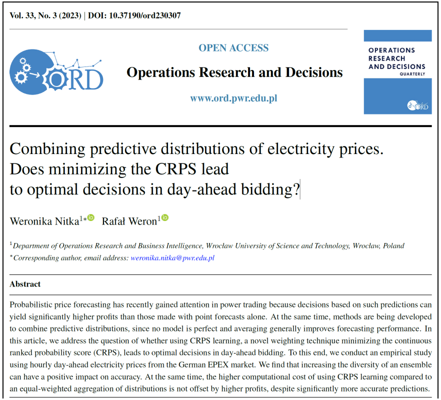
Does CRPS learning lead to higher trading profits?

(Nitka & Weron, 2023, ORD)

% change in the CRPS and profits per trade when using CRPS learning (instead of naive averaging)

	CRPS	Profits/trade (EUR/MWh) 50% PI	70% PI	90% PI
Ensemble #1	0.0%	-1.1%	-0.8%	-3.6%
Ensemble #2	-0.1%	-0.6%	-0.8%	-2.5%
Ensemble #3	-0.7%	-1.7%	-1.5%	-6.3%
Ensemble #4	-0.4%	-2.1%	-1.4%	-2.8%
Ensemble #5	0.2%	-0.5%	-0.1%	-5.0%
Ensemble #6	-0.8%	-0.4%	-1.0%	-4.3%

- CRPS learning yields **lower** CRPS → **good**
- CRPS learning yields **lower** profits → **bad**



Vol. 33, No. 3 (2023) | DOI: 10.37190/ord230307

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OPERATIONS RESEARCH AND DECISIONS QUARTERLY

Combining predictive distributions of electricity prices. Does minimizing the CRPS lead to optimal decisions in day-ahead bidding?

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Abstract

Probabilistic price forecasting has recently gained attention in power trading because decisions based on such predictions can yield significantly higher profits than those made with point forecasts alone. At the same time, methods are being developed to combine predictive distributions, since no model is perfect and averaging generally improves forecasting performance. In this article, we address the question of whether using CRPS learning, a novel weighting technique minimizing the continuous ranked probability score (CRPS), leads to optimal decisions in day-ahead bidding. To this end, we conduct an empirical study using hourly day-ahead electricity prices from the German EPEX market. We find that increasing the diversity of an ensemble can have a positive impact on accuracy. At the same time, the higher computational cost of using CRPS learning compared to an equal-weighted aggregation of distributions is not offset by higher profits, despite significantly more accurate predictions.

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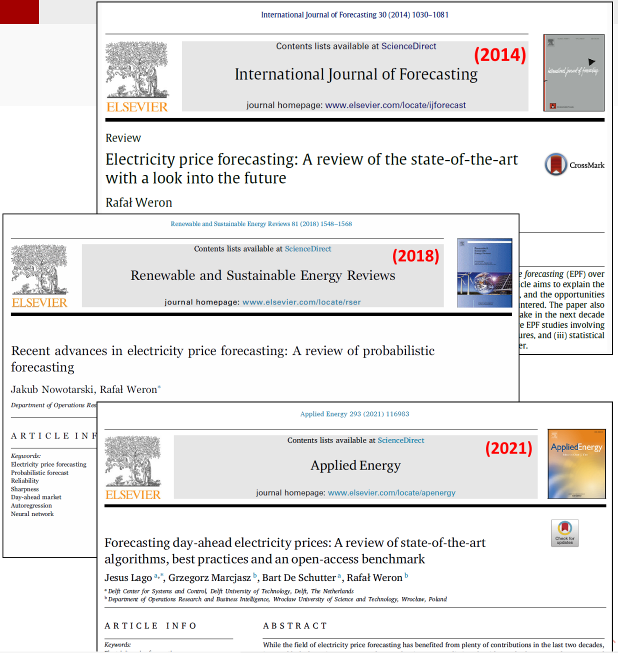

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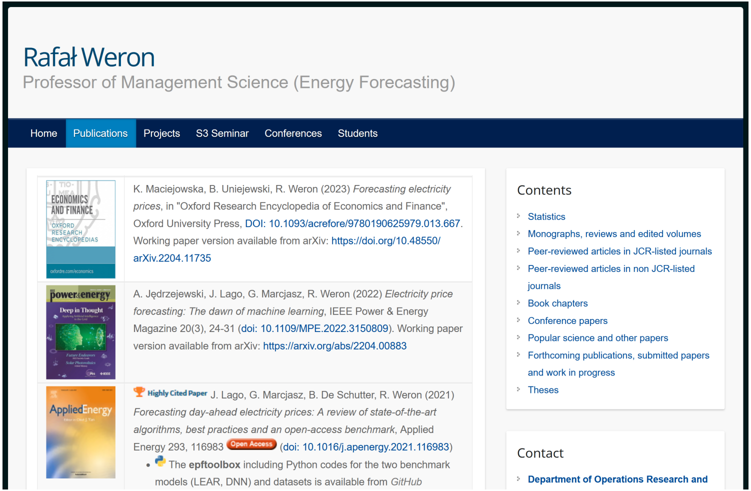
Articles & working papers on https://p.wz.pwr.edu.pl/∼weron.rafal/Publ



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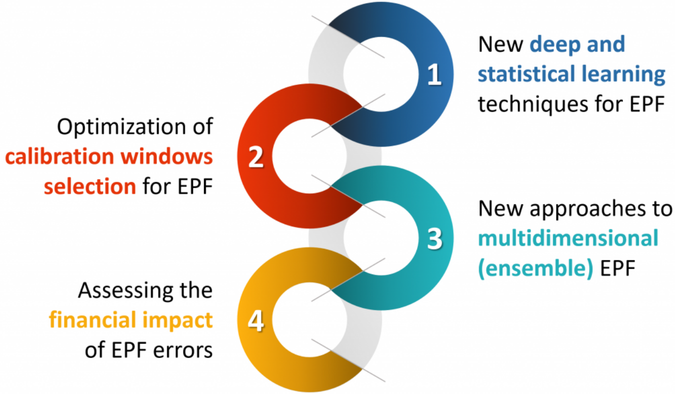
CrossFIT (2019-2025)

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 prIce fORecasting In electriciTY markets
(https://kbo.pwr.edu.pl/en/research/research-projects/dfg-ncn-2021-43-i-hs4-02578-2)