Crossing Frontiers in electricity prIce forecasTing (CrossFIT),
czyli przekraczanie granic w prognozowaniu cen energii elektrycznej

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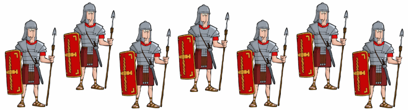
https://p.wz.pwr.edu.pl/~weron.rafal

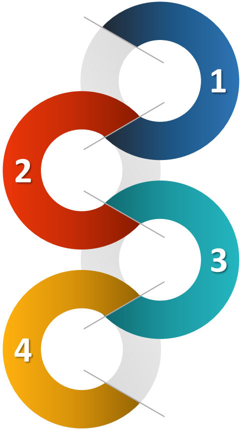


* Based on joint work with K.Bilińska, Y.Chawla, K.Chęć, A.Lipiecki, K.Maciejowska, W.Nitka, T.Serafin, B.Uniejewski, P.Zaleski (Wrocław Tech), C.Challu, K.Olivares (Nixtla), T.Hong (UNCC), K.Hubicka (UBS), A.Jędrzejewski (U.Aveiro), C.Kath (RWE), J.Lago (Amazon), G.Marcjasz (Alpiq), M.Narajewski (Statkraft), J.Nasiadka (Nokia), J.Nowotarski (BNY Mellon), H.Zareipour (U.Calgary), F.Ziel (U.Duisburg-Essen)

** Julia/Python notebooks coded by A.Lipiecki

CrossFIT (2019-2026)

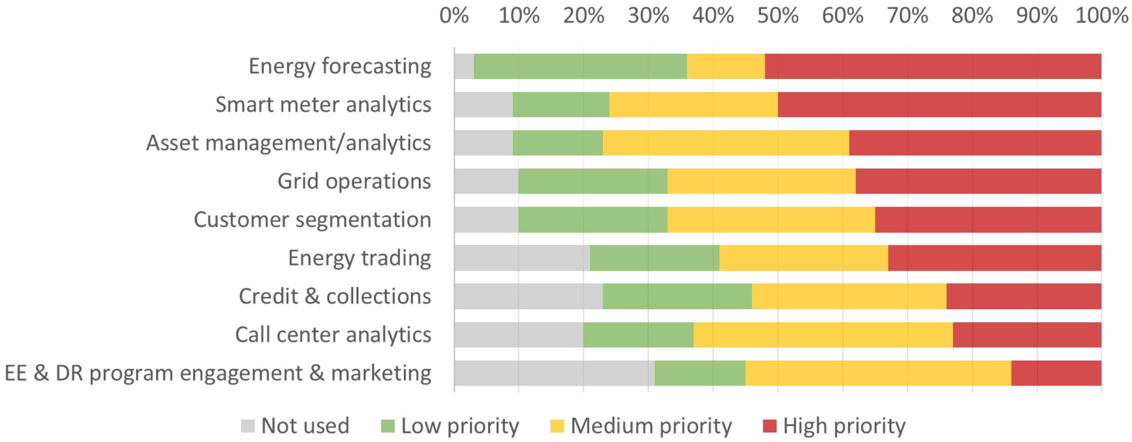
(https://kbo.pwr.edu.pl/en/research/research-projects/ncn-2018-30-a-hs4-00444)



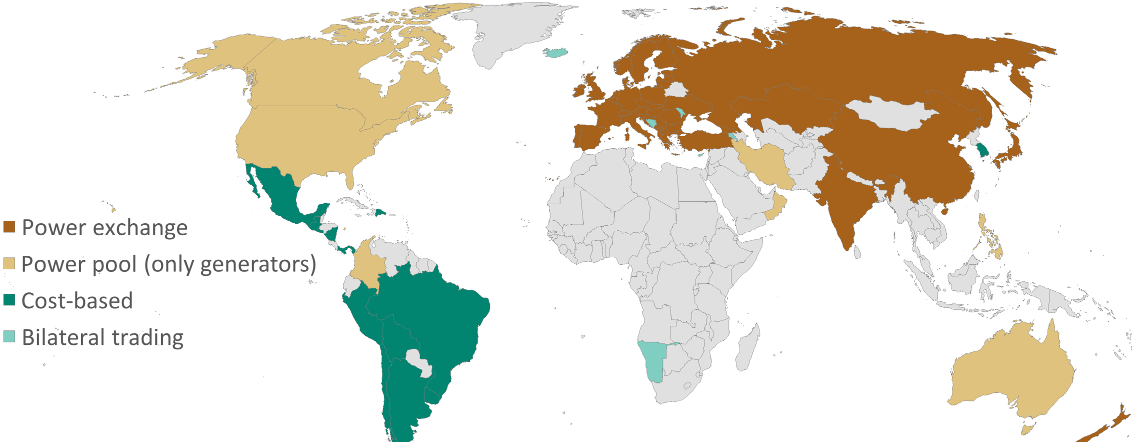
1. New **deep and statistical learning** techniques for EPF
2. Optimization of **calibration windows selection** for EPF
3. New approaches to **multidimensional (ensemble)** EPF
4. Assessing the **financial impact** of EPF errors

Energy forecasting is a top priority for utilities

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

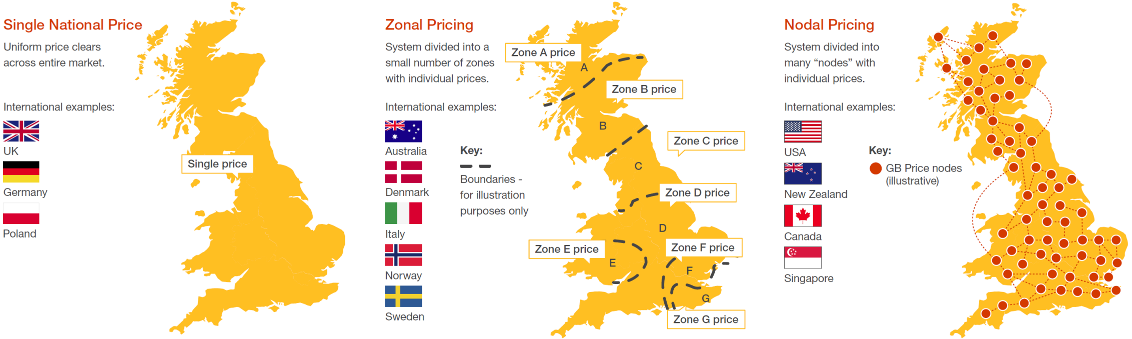


Competitive power market structures across the globe



Data source: Akcura (2024)
Global Power Market Structures Database

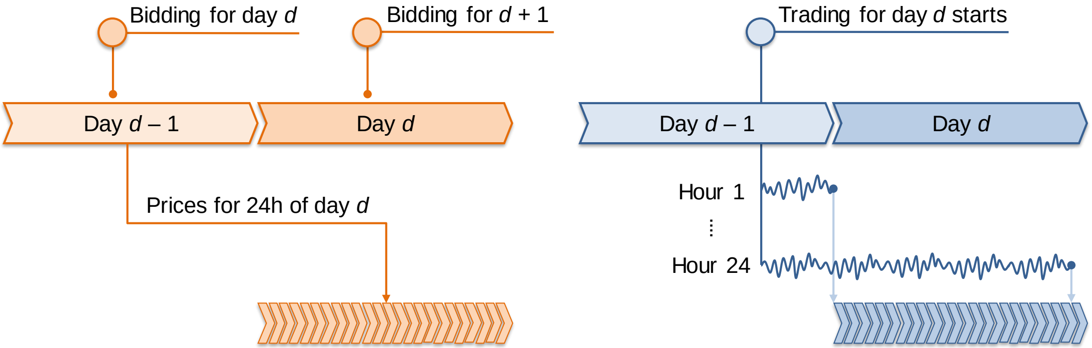
National vs. zonal vs. nodal pricing



Adapted from: National Grid ESO (2022) *Net Zero Market Reform*

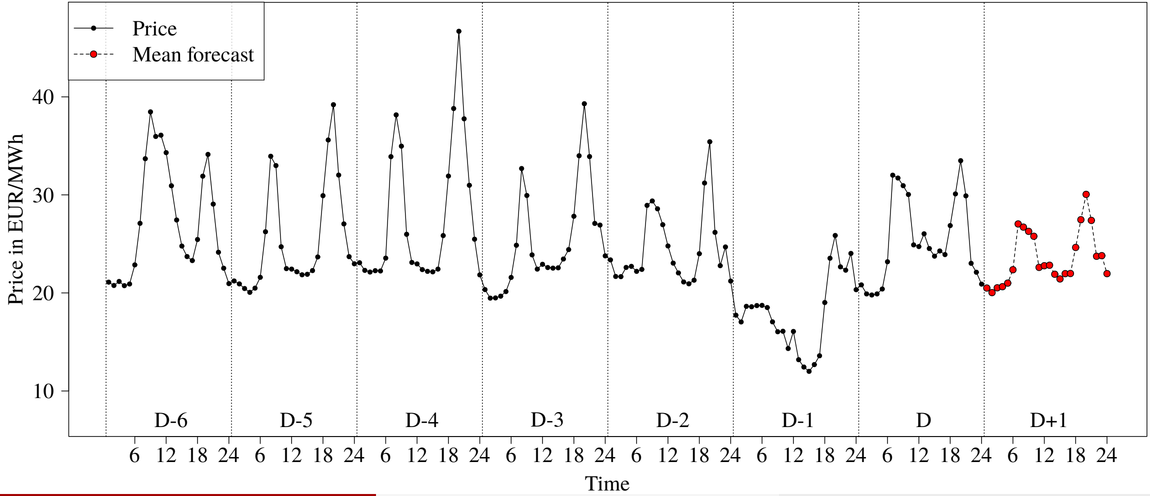
Day-ahead (> 90% of papers) vs. intraday (real-time) markets

(Maciejowska, Uniejewski & Weron, 2023, Oxford Res. Enc.)

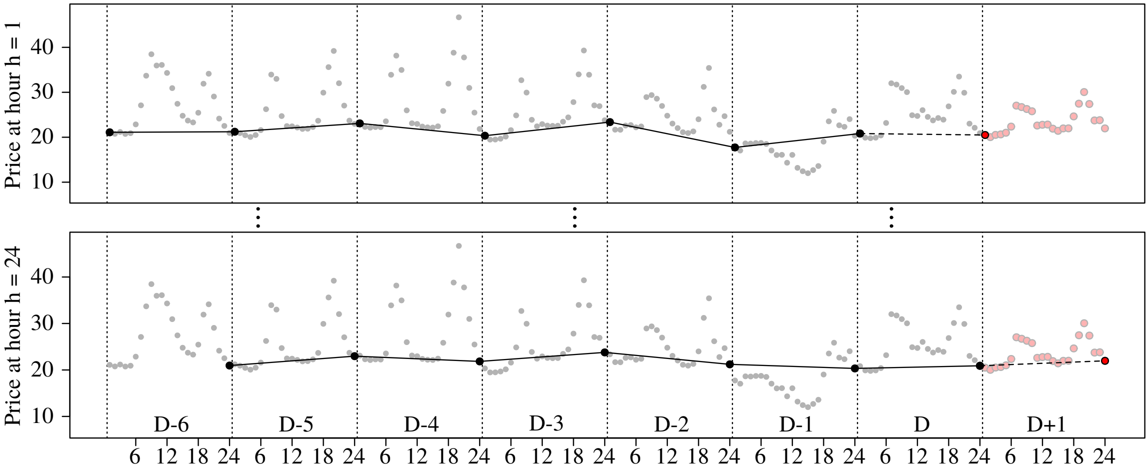


Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)

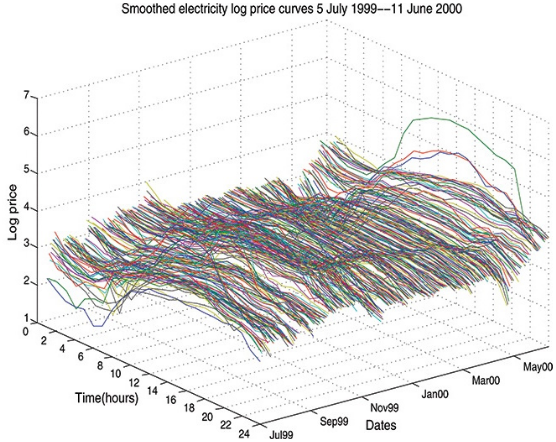


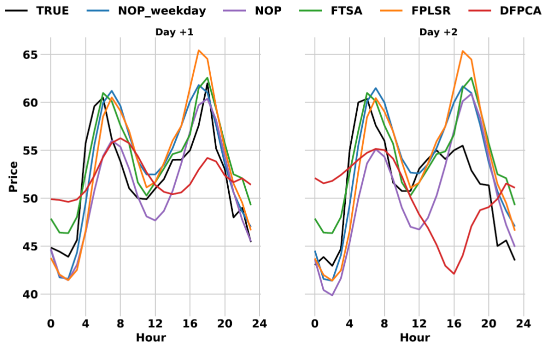
... multivariate ...



... functional (data analysis) ...

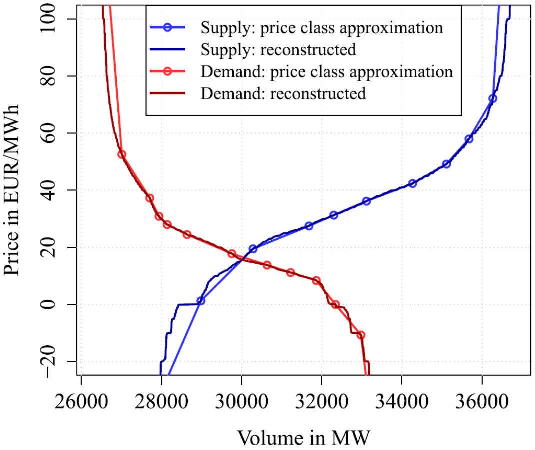
(Chen & Li, 2017, JBES; Chen et al., 2019, Ann.Appl.Stat; Wang & Cao, 2023, Environmetrics)

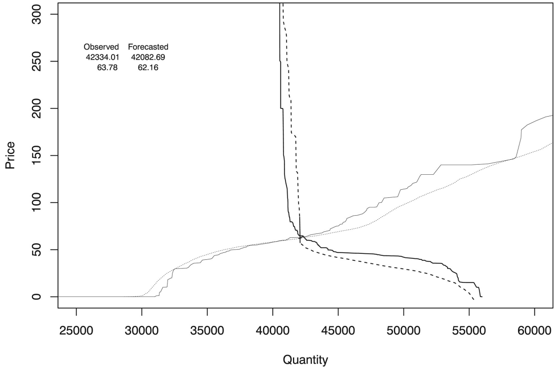




... or supply & demand curves?

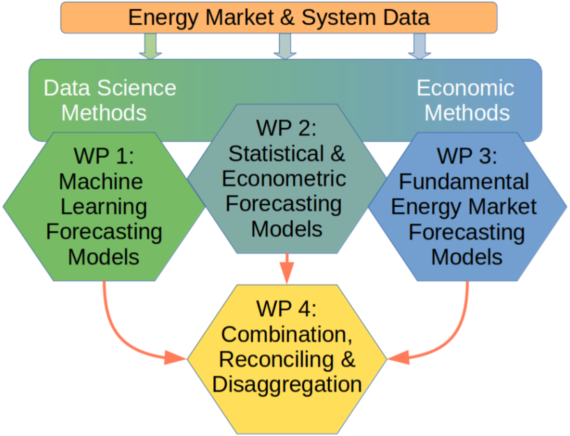
(Ziel & Steinert, 2016, ENEECO → 'X-model'; Shah & Lisi, 2020, J.Forecasting)





What about mid- and long-term forecasts?

PRobabilistic mid- and long-term prIce fORecasting In electriciTY markets (**PRIORITY**)
(https://kbo.pwr.edu.pl/en/research/research-projects/dfg-ncn-2021-43-i-hs4-02578-2)



Up to year-ahead with ML/econometric models

Mean Absolute Errors for 04.2018-04.2024 (Ghelasi & Ziel, 2025, RSER, Tab. 8)

Autoregression (horizons 1–14) | Futures (fuel, CO2) (horizons 30–150) | Weekly dummies (+ seasonal RES/Load) (horizons 150–360)

Model name	Variables: Week Dummies	Variables: Annual Seasons	Variables: Autoreg	Variables: RES & Load	Variables: Fuels	Method: Unconstrained	Method: Constrained	Method: Current	Forecasting horizon (days): 1	7	14	30	60	90	120	150	180	210	240	270	300	330	360
Naive									26.57	33.02	37.52	43.89	49.26	53.16	58.08	59.51	63.50	65.20	67.43	67.31	72.39	76.25	76.58
WD	×					×			60.46	60.41	60.59	61.12	61.66	62.08	62.62	62.86	62.97	63.15	63.33	63.41	63.36	63.42	63.41
Expert	×	×	×	×	×	×			16.60	29.57	34.58	45.79	49.25	61.48	65.82	76.08	95.87	117.70	128.18	127.45	160.40	175.30	163.87
Constr	×	×	×	×	×		×		**16.58**	**29.47**	**33.85**	41.98	47.26	57.16	64.53	71.10	84.07	91.07	105.95	116.76	125.44	130.59	130.45
Current	×	×	×	×	×		×	×	16.74	32.23	35.61	**40.31**	**44.70**	**49.12**	**52.62**	**56.02**	61.02	65.55	69.00	67.83	72.38	73.58	75.05
WD+RL	×			×			×		50.74	57.88	59.27	60.73	61.51	62.48	61.10	59.34	**58.95**	**58.34**	**60.23**	**59.99**	**61.73**	62.86	63.29
WD+RL+C	×			×			×	×	53.19	57.93	58.21	58.86	59.57	60.13	60.62	60.91	60.91	60.97	61.25	61.57	61.80	**62.12**	**62.52**
WD+ARL+C	×		×	×			×	×	17.18	32.81	37.10	42.56	48.47	52.52	58.06	65.06	73.92	85.39	100.60	110.33	122.11	130.11	129.15
NeuralNet	×	×	×	×	×	×			20.88	39.34	48.70	58.07	61.60	70.50	87.87	110.80	119.74	132.82	150.41	158.95	130.62	132.21	134.69
XGBoost	×	×	×	×	×	×			23.55	44.58	46.26	48.25	46.97	53.41	60.03	62.48	66.97	68.56	71.71	74.95	73.17	72.74	83.43

Beyond one year: Survey of Professional Energy Forecasters

Ankieta nt. hurtowych cen energii elektrycznej i gazu w latach 2024-2035

Zapraszamy do udziału w anonimowej ankiecie wzorowanej na "Survey of Professional Forecasters" Europejskiego Banku Centralnego, której celem jest uzyskanie informacji na temat oczekiwań co do hurtowych cen energii elektrycznej i gazu w Polsce w latach 2024-2035.

Yash Chawla, Rafał Weron
Katedra Badań Operacyjnych i Inteligencji Biznesowej, Politechnika Wrocławska

Hurtowe ceny energii elektrycznej w kolejnych latach (PLN/MWh)

Cena energii elektrycznej w 2023 *

533,62

Cena energii elektrycznej w 2024 *

W PLN, do 2 miejsc po przecinku

Hurtowe ceny gazu w kolejnych latach (PLN/MWh)

Cena gazu w 2023 *

213,94

Cena gazu w 2024 *

W PLN, do 2 miejsc po przecinku

Cena gazu w 2025 *

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ELSEVIER
Journal of Cleaner Production
journal homepage: www.elsevier.com/locate/jclepro
Cleaner Production

Cost-benefit analysis of a municipal waste management project: Using a survey of professional forecasters to provide reliable projections until 2035

Yash Chawla [a,*], Katarzyna Chojnacka [b], Michał Paca [c], Anna Pudełko [c], Rafał Weron [a], Przemysław Zaleski [a,d]

[a] Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology, 50-370, Wrocław, Poland
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A R T I C L E I N F O

Handling Editor: Cecilia Maria Villas Bôas de Almeida

Keywords:
Municipal solid waste
Biogas plant
Cost-benefit analysis
Professional forecasters survey

A B S T R A C T

The widespread adoption of selective kitchen and garden waste processing in closed biogas plants is often hindered by financial feasibility and social acceptance. This study presents a comprehensive cost-benefit analysis of waste processing through wet and dry fermentation, evaluating energy recovery options from combined heat and power and compressed natural gas installations. Drawing on data from a Polish investment project and a novel concept in waste management research – a survey of professional energy forecasters, we provide financial projections until 2035 to guide sustainable decision-making. Our results emphasize the economic viability of bio-based energy recovery technologies, while also highlighting the potential social and environmental benefits. By diverting waste from landfills and recovering energy, biogas plants contribute to both energy transition goals and the broader objectives of sustainable waste management, including improved resource efficiency and reduced reliance on fossil fuels. This study offers practical insights for municipalities and businesses, promoting policies that support public-private partnerships and the long-term viability of renewable energy projects within the circular economy framework.

1. Introduction

In an era of resource scarcity, re-evaluating our approach to waste management is imperative. Landfilling, the traditional approach for managing municipal solid waste, conflicts with contemporary circular economy (CE) principles (Bertanza et al., 2021). Despite discussions on extracting energy from landfilled waste (Kurniawan et al., 2022), escalating costs of landfilling and increasingly stringent regulations demand alternatives.

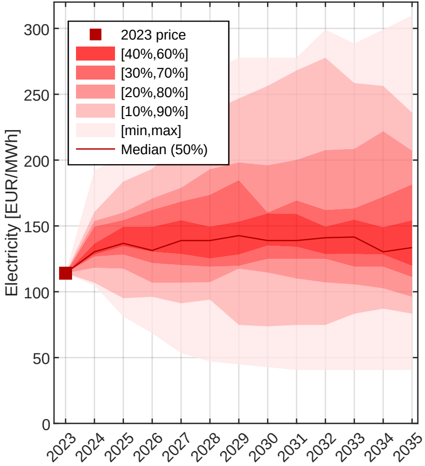
The circular economy not only promotes resource efficiency but also raises important social and environmental justice concerns. The current linear economy unequally distributes the environmental and social costs associated with energy and material provision, disproportionately affecting vulnerable groups such as low-income communities, which often face higher exposure to environmental hazards and energy poverty (Ashton et al., 2022; Sovacool, 2021). Transitioning to a CE must therefore address these inequalities by ensuring equitable access to resources, energy, and waste management services, leaving no one behind (Schröder et al., 2020).

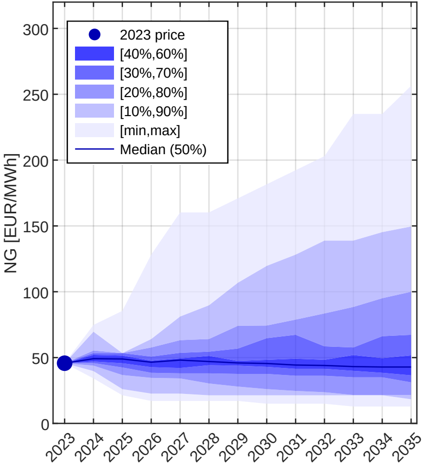
In this context, biogas production from organic waste represents a promising pathway for achieving both environmental sustainability and social equity. By diverting bio-based waste from landfills to anaerobic digestion in closed biogas plants, we can recover energy and materials while mitigating environmental impacts (Ibarra-Esparza et al., 2023; Kumar and Samadder, 2017; Skrzypczak et al., 2023). This approach aligns with CE principles and contributes to the energy transition by reducing reliance on fossil fuels, while ensuring that the benefits—such as cleaner energy and reduced pollution—are accessible to all, particularly marginalized communities affected by energy poverty.

Despite significant advances in waste management strategies and material recovery (Fraccascia et al., 2021), a notable gap remains in empirical research supporting the practical implementation of these technologies (Andeobu et al., 2022). This gap is exacerbated by the dominance of a few players in the waste management market and the

Survey of Professional Energy Forecasters cont.

(Chawla et al., 2025, JCP)



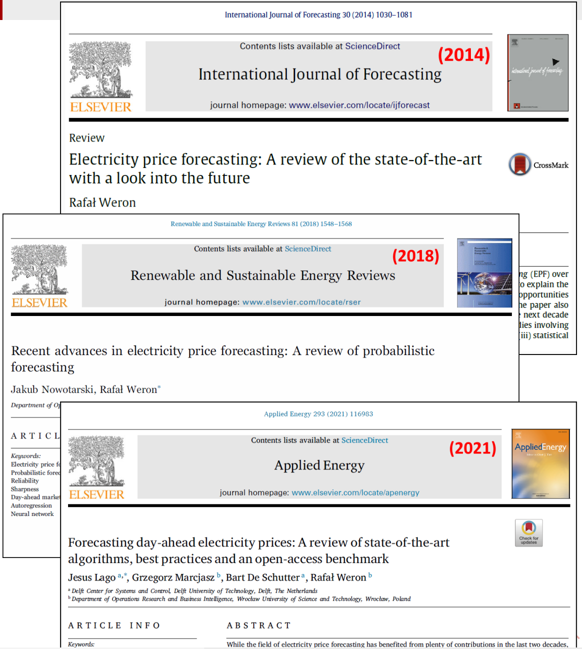


1 Introduction

2 Model evolution

- (Auto)regressive models
- Averaging across windows
- LASSO-Estimated AR (LEAR)
- Deep and interpretable ML

3 Beyond point forecasts



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

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Review

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

Rafał Weron

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

Contents lists available at ScienceDirect

(2018)

Renewable and Sustainable Energy Reviews

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

Jakub Nowotarski, Rafał Weron*

Applied Energy 293 (2021) 116983

Contents lists available at ScienceDirect

(2021)

Applied Energy

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

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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

ABSTRACT

Keywords:

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

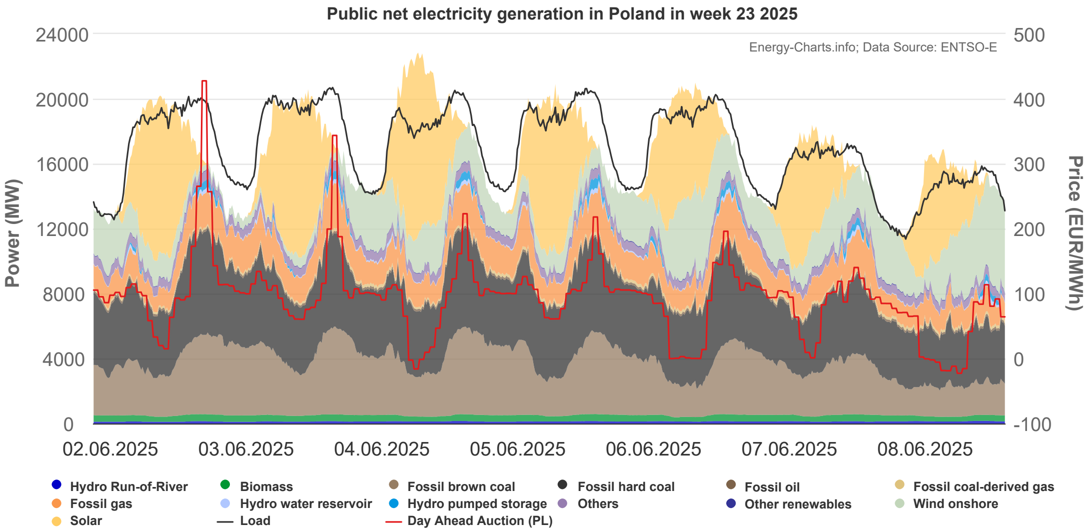
Expert ARX-type models

The workhorse of EPF – autoregressive structure with exogenous variables:

$$P_{d,h} = \beta_0 + \underbrace{\sum_{i=1}^{7} \beta_i P_{d-i,h}}_{\text{AutoRegressive effects}} + \underbrace{\sum_{i=1}^{7} \beta_{i+7} D_i}_{D_1 = \text{Mon}, \ldots} + \underbrace{\sum_{i=1}^{K} \beta_{i+14} X^{(i)}_{d,h}}_{\text{eXogenous variables}} + \varepsilon_{d,h}$$

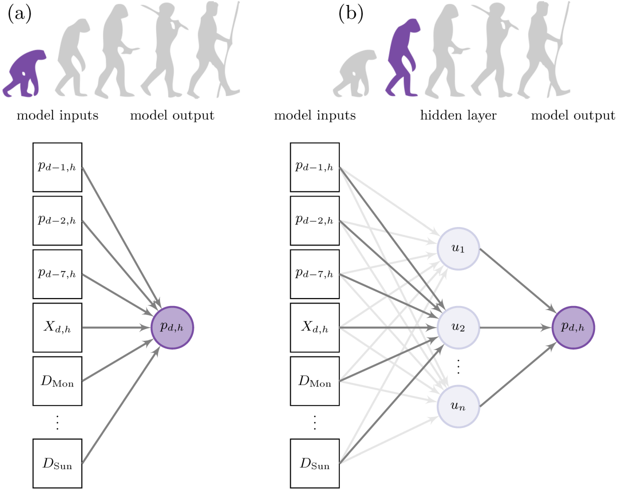
- Special cases:
  - Naive model $P^{(1)}_{d,h}$ for $\beta_1 = 1$ and $\beta_{i \neq 1} = 0$
  - AR(7), sparse AR(7) with some AR lags missing
  - ARX(7) with $K \geqslant 1$, sparse ARX(7) with some AR lags missing

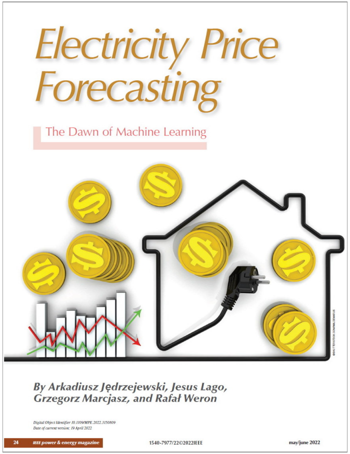
Do we need exogenous variables?



Linear regression vs. single-output (shallow) neural network

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




Electricity Price Forecasting

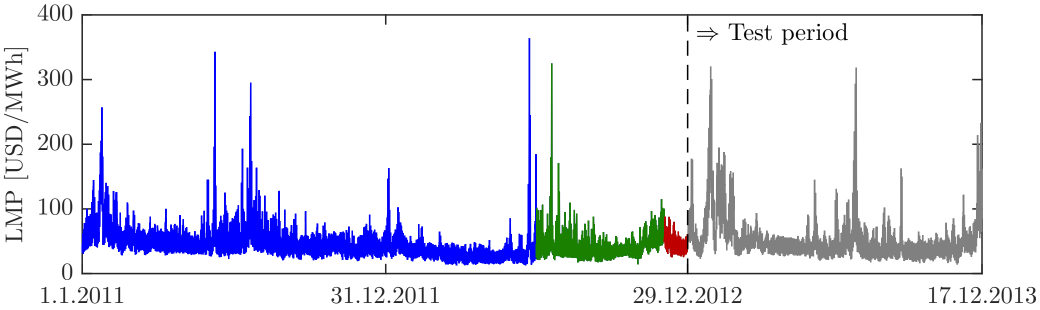
The Dawn of Machine Learning

By Arkadiusz Jędrzejewski, Jesus Lago, Grzegorz Marcjasz, and Rafał Weron

Digital Object Identifier 10.1109/MPE.2022.3150809
Date of current version: 19 April 2022

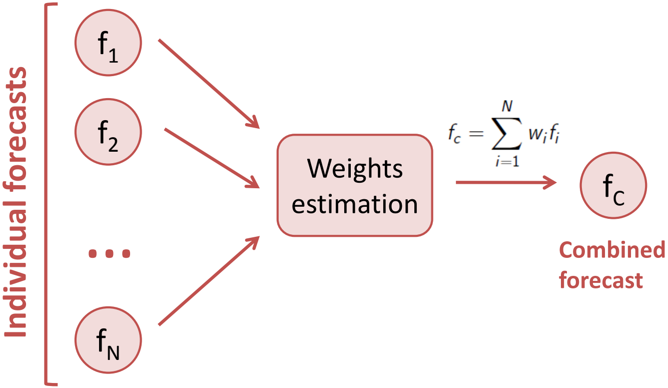
24 IEEE power & energy magazine 1540-7977/22©2022IEEE may/june 2022

What is the optimal calibration (training) window size?



- 728-day vs. 182-day vs. 28-day calibration window
- Longer windows → better reflect trends, more stable parameters
- Shorter windows → quicker adapt to changes in price dynamics

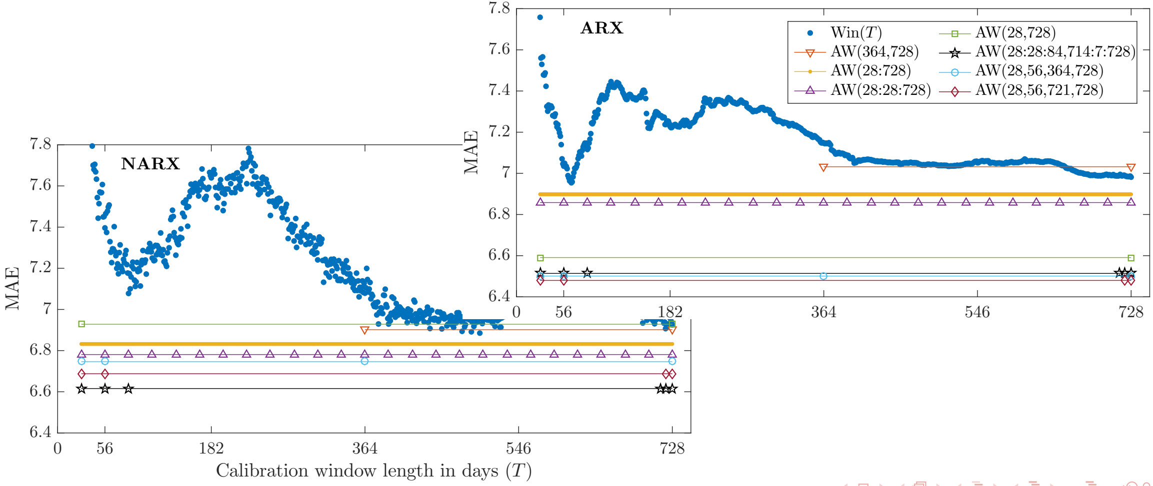
Point forecast averaging: The idea



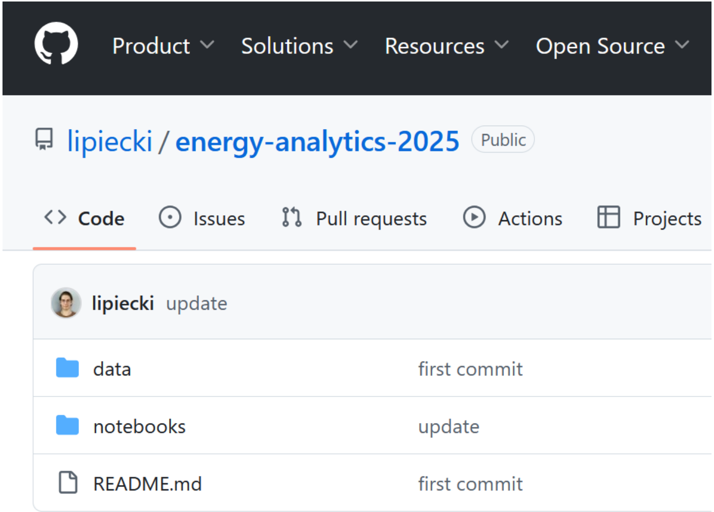
- Dates back to the works of Bates, Crane, Crotty & Granger (1960s)
- 'Statistical/Econometric world': *combining forecasts*, *forecast averaging* (not *model averaging*)
- 'AI/Engineering world': *committee machines*, *ensemble averaging*, *expert aggregation*

Simple averaging across calibration windows

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



IIF Distinguished Lectures on EPF: Averaging.ipynb



Experiment yourself:

What is shrinkage (regularization)?

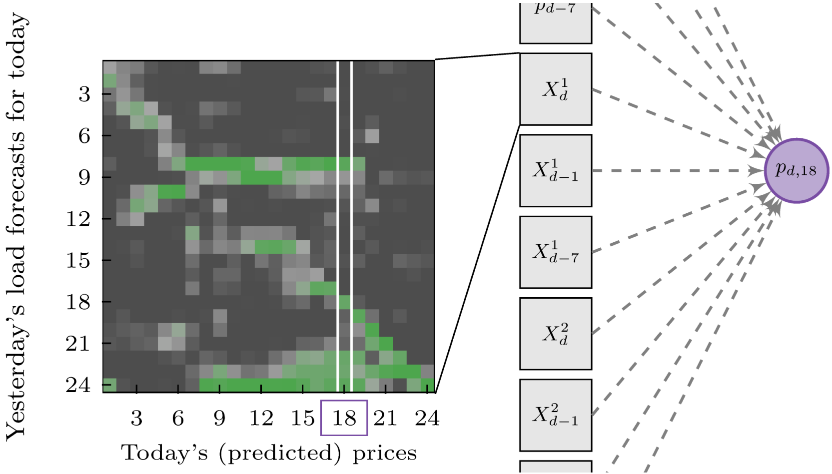
- Minimize the residual sum of squares (RSS $\equiv$ sum of squared errors) $+$ a penalty function of the betas:

$$\hat{\beta} = \underset{\beta_j}{\operatorname{argmin}} \left\{ \underbrace{\sum_{i=1}^{N} \left(y_i - \sum_{j=1}^{p} \beta_j x_{i,j} \right)^2}_{RSS} + \lambda \underbrace{\sum_{j=1}^{n} |\beta_j|^q}_{penalty} \right\}$$

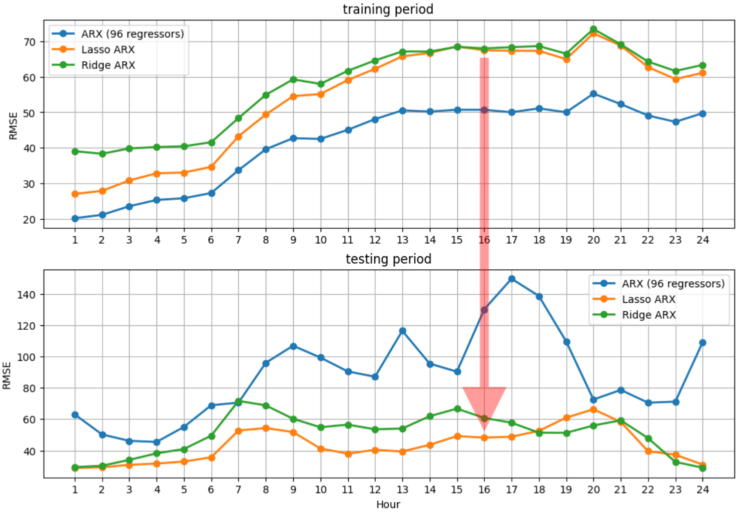
  where $\lambda \geqslant 0$ is a tuning (or regularization) parameter
- Most popular:
  - $q = 2 \rightarrow$ Ridge regression (Hoerl & Kennard, 1970, Technometrics)
  - $q = 1 \rightarrow$ Least absolute shrinkage & selection operator (Tibshirani, 1996, JRSSB)

LASSO-Estimated AR (LEAR): Variable importance

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



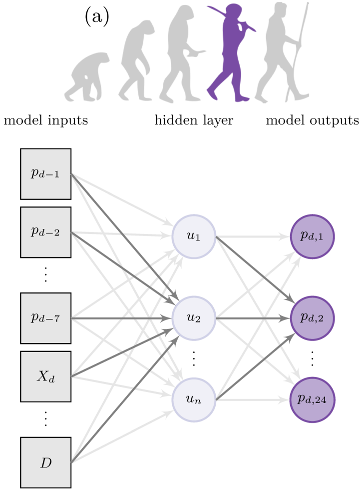
IIF Distinguished Lectures: Shrinkage.ipynb

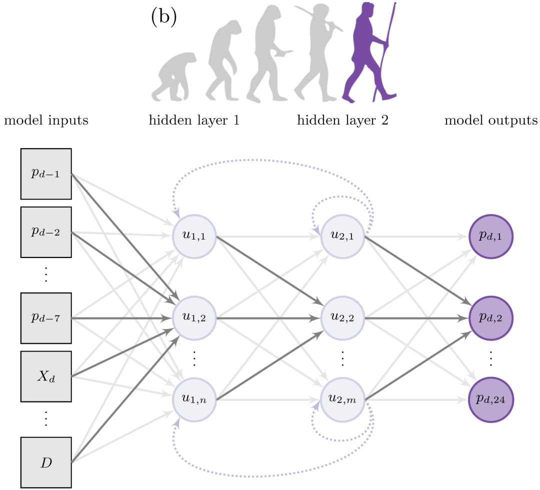


Experiment yourself:

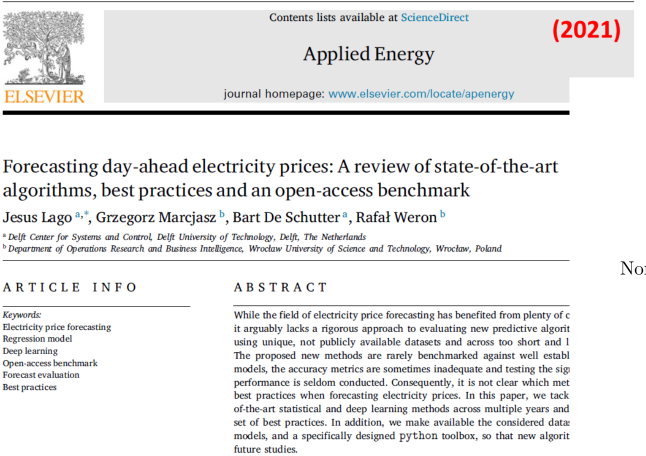
Multi-output shallow and deep neural networks (DNNs)

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





What about performance?


Contents lists available at ScienceDirect

(2021)

Applied Energy

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

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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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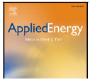
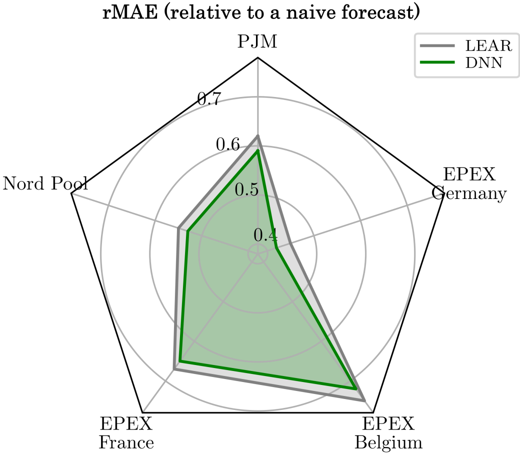
ARTICLE INFO

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

ABSTRACT

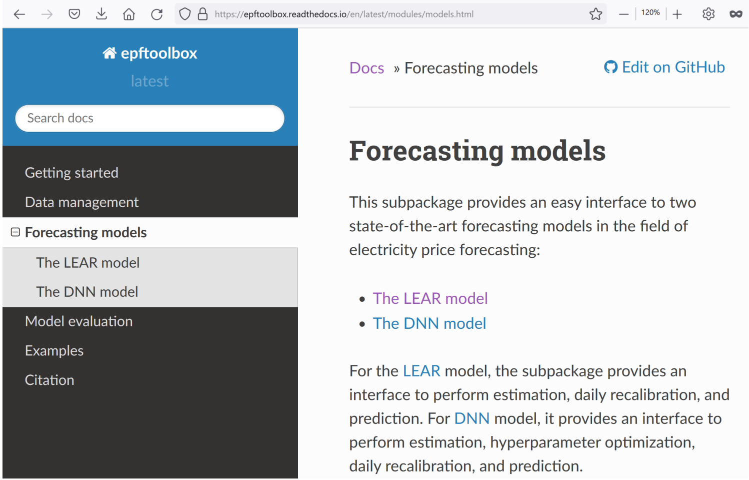
While the field of electricity price forecasting has benefited from plenty of c
it arguably lacks a rigorous approach to evaluating new predictive algorit
using unique, not publicly available datasets and across too short and l
The proposed new methods are rarely benchmarked against well establ
models, 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

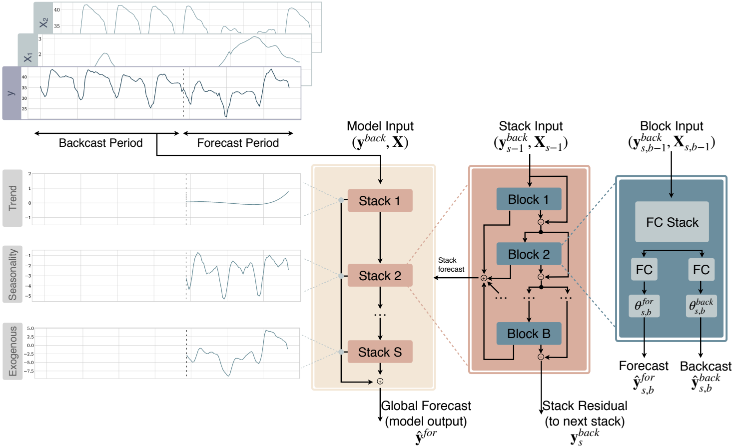
(Lago, Marcjasz, De Schutter & Weron, 2021, APEN)



Experiment yourself:

Interpretable AI: NBEATSx

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



Experiment yourself:

1 Introduction

2 Model evolution

3 Beyond point forecasts

- Do we need probabilistic forecasts?
- Postprocessing point forecasts
- Quantile Regression Averaging
- Combining probabilistic forecasts
- Distributional Deep Neural Nets

International Journal of Forecasting 30 (2014) 1030–1081
Contents lists available at ScienceDirect
International Journal of Forecasting
journal homepage: www.elsevier.com/locate/ijforecast

(2014)

Review

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

Rafał Weron

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Renewable and Sustainable Energy Reviews 81 (2018) 1548–1568
Contents lists available at ScienceDirect
Renewable and Sustainable Energy Reviews
journal homepage: www.elsevier.com/locate/rser

(2018)

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

Jakub Nowotarski, Rafał Weron*
Department of Op

ARTICL

Keywords:
Electricity price f
Probabilistic forec
Reliability
Sharpness
Day-ahead market
Autoregression
Neural network

Applied Energy 293 (2021) 116983
Contents lists available at ScienceDirect
Applied Energy
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

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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,

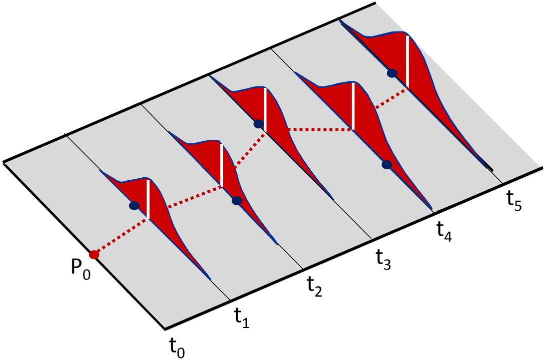
Probabilistic (interval, density) forecasting

(Gneiting & Katzfuss, 2014, Annu Rev)

We cannot observe the true underlying distribution $\Rightarrow$ we cannot compare the *predictive distribution* $\hat{F}$ with the actual one F ... only with past observations

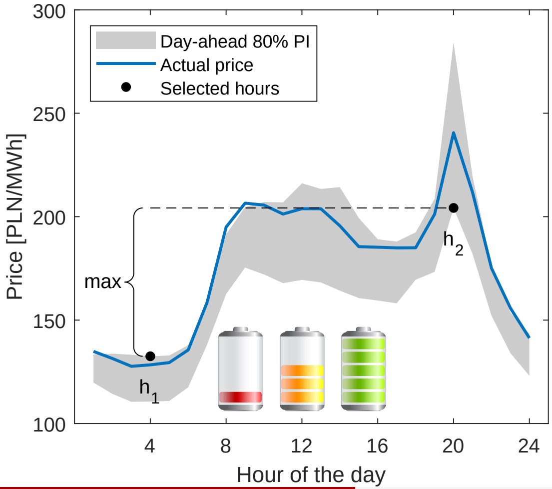
Gneiting et al. (2007a, 2007b, 2014) argue that probabilistic forecasting aims to '*maximize the **sharpness** of the predictive distributions, subject to **reliability***'

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



Do we need probabilistic forecasts?

(Uniejewski & Weron, 2021, ENEECO)



Quantile-based trading strategy

Simultaneously bid day-ahead:

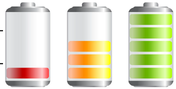
- buy 1 MW for $\hat{P}^{1-\alpha}_{d,h_1}$ at hour h_1
- sell 0.8 MW at $\hat{P}^{\alpha}_{d,h_2}$ at hour h_2

$\leftarrow$ 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)

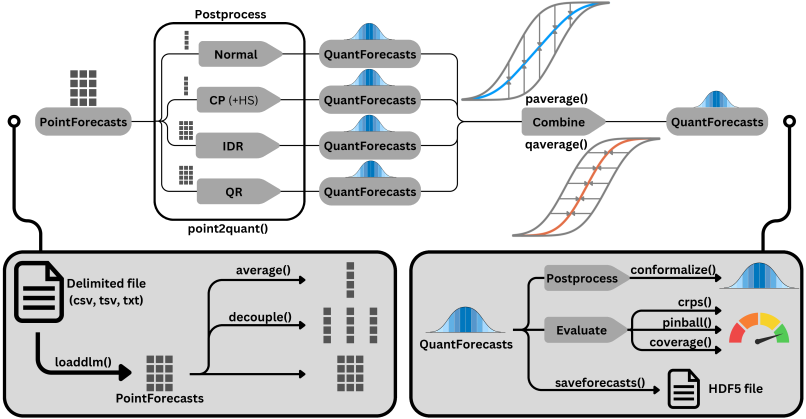


Strategy			**Profit**		
Naive (4am–12pm)			33 065.29		
Point forecasts-based			33 722.39		
Quantile-based	1-99%	5-95%	10-90%	20-80%	25-75%
Q-Ave	41 317.92	43 328.89	43 432.31	43 289.09	43 033.88
F-Ave	39 848.26	43 369.44	44 052.04	44 088.11	43 130.34
QRM	41 163.29	43 054.28	43 124.12	43 731.54	42 240.25
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

Quantile-based trading yields 19-34% higher profits than point forecasts-based!

Postprocessing point forecasts with PostForecasts.jl

(Vannitsem et al., 2018, Elsevier; Lipiecki et al., 2024, ENEECO; Lipiecki & Weron, 2025, SoftwareX)



Experiment yourself:

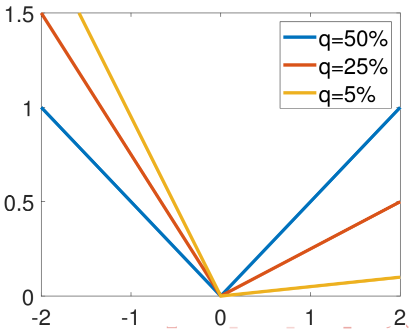
Evaluating reliability & sharpness

(Gneiting & Raftery, 2007, JASA; Nowotarski & Weron, 2018, RSER; Nitka & Weron, 2023, ORD)

- Pinball score (also linlin/bilinear/newsboy/quantile loss/score, check function):

$$\mathrm{PS}\left(\hat{q}, x, q\right) = \left(\mathbb{1}_{\{x<\hat{q}\}} - q\right)\left(\hat{q} - x\right) = \begin{cases} (1-q)\left(\hat{q}-x\right) & \text{for } x < \hat{q} \\ q\left(x-\hat{q}\right) & \text{for } x \geqslant \hat{q} \end{cases}$$

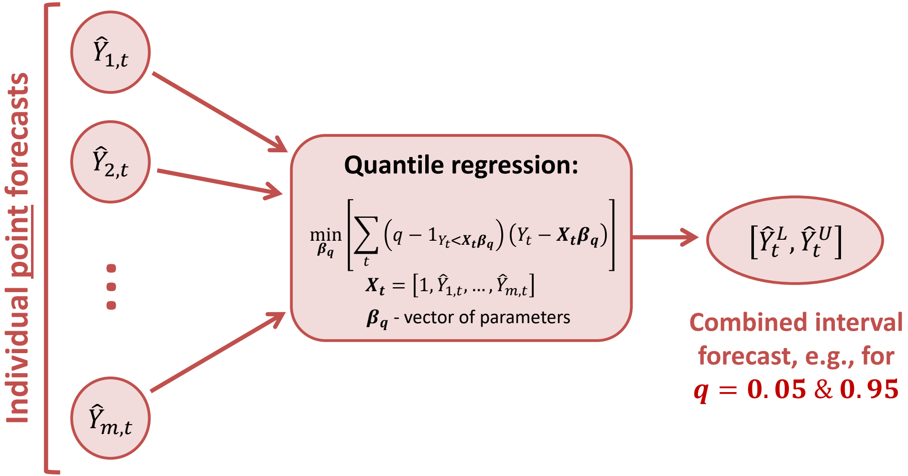
where $\hat{q} \equiv \hat{F}^{-1}(q)$ is the quantile forecast



- For an Aggregate PS (or APS) average:
  - over t in the test period
  - over $q_1 < \ldots < q_M$ quantiles $\rightarrow$ CRPS

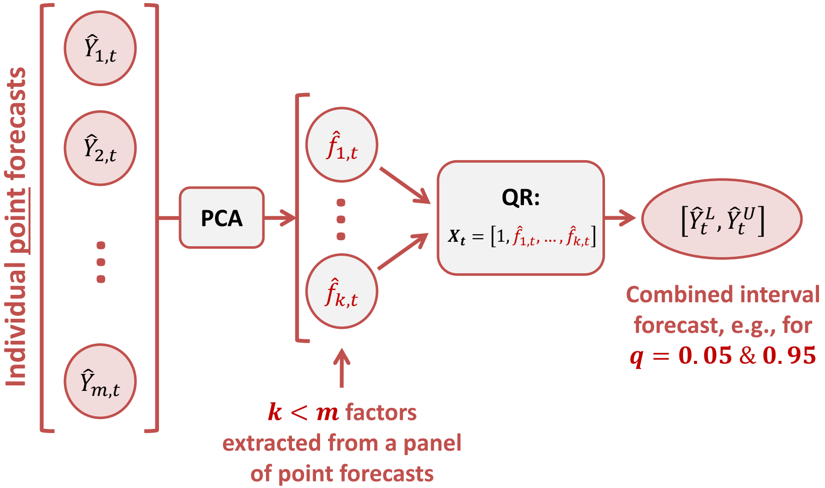
Quantile Regression Averaging (QRA): The idea

(Nowotarski & Weron, 2015, COST)



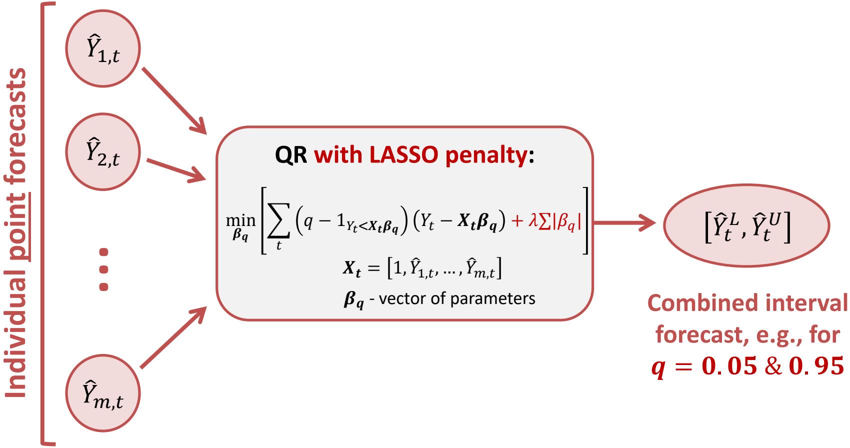
Factor QRA (FQRA): When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



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

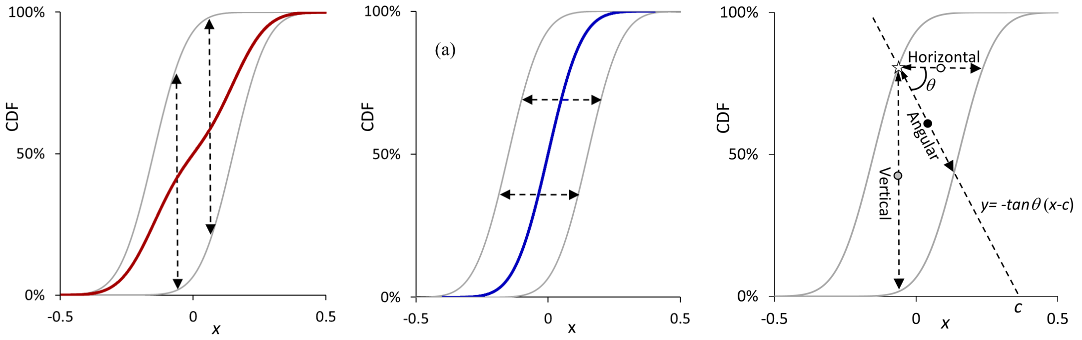
(Uniejewski & Weron, 2021, ENEECO) $\sim$ 5% improvement over QRA



Combining probabilistic forecasts is tricky ...

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

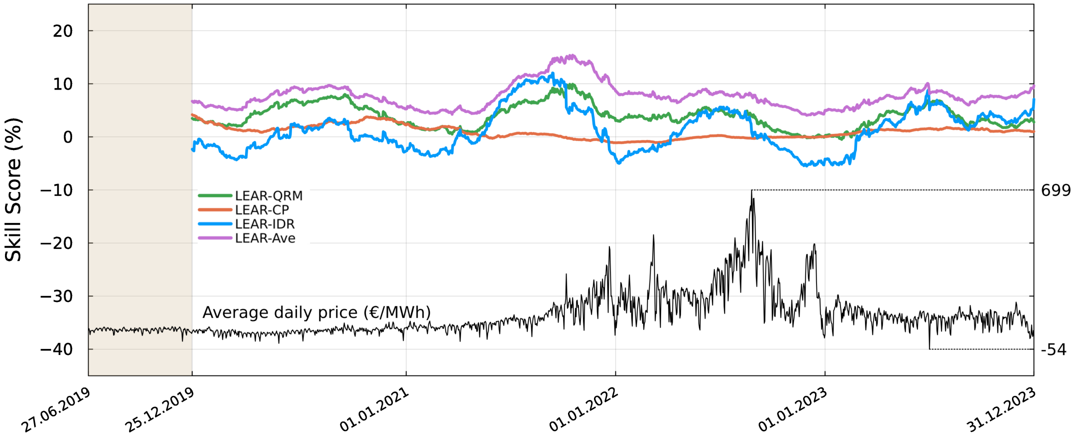
Vertical (over probabilities), **horizontal** (quantiles → sharper CDF) ... or at any angle



... but can be beneficial

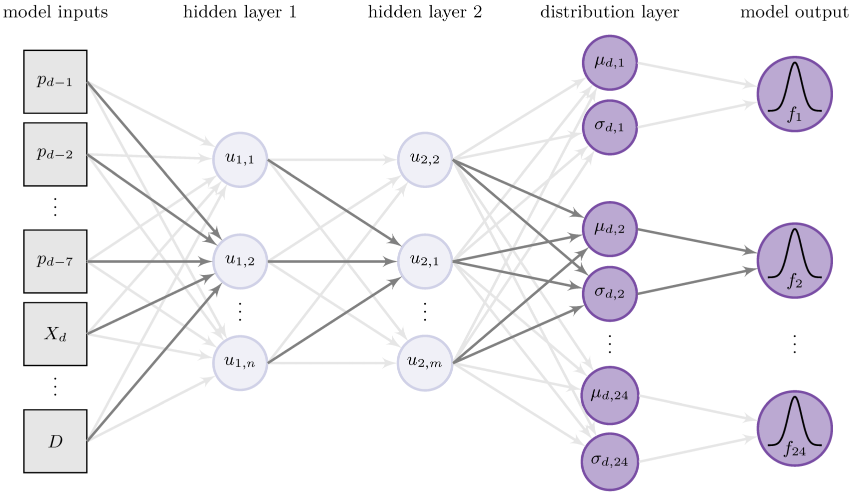
(Lipiecki, Uniejewski & Weron, 2024, ENEECO; illustrated here using EPEX-DE data)

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

ELSEVIER

Contents lists available at ScienceDirect

Energy Economics

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

Distributional neural networks for electricity price forecasting

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ARTICLE INFO

JEL classification:
C44
C45
C46
C22
C53
Q47

Keywords:
Distributional neural network
Probabilistic forecasting

ABSTRACT

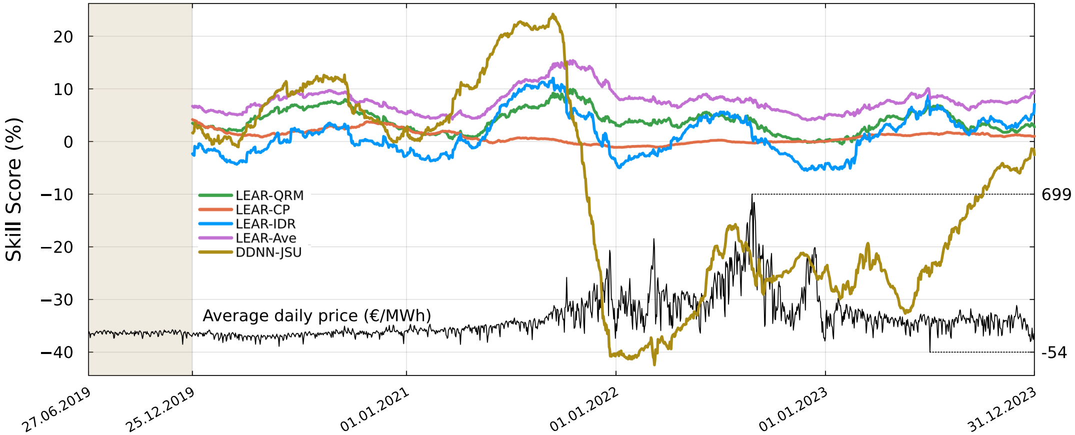
We present a novel approach to probabilistic electricity price forecasting which utilizes distributional neural networks. The model structure is based on a deep neural network containing a so-called probability layer, i.e., the outputs of the network are parameters of the normal or Johnson's SU distribution. 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

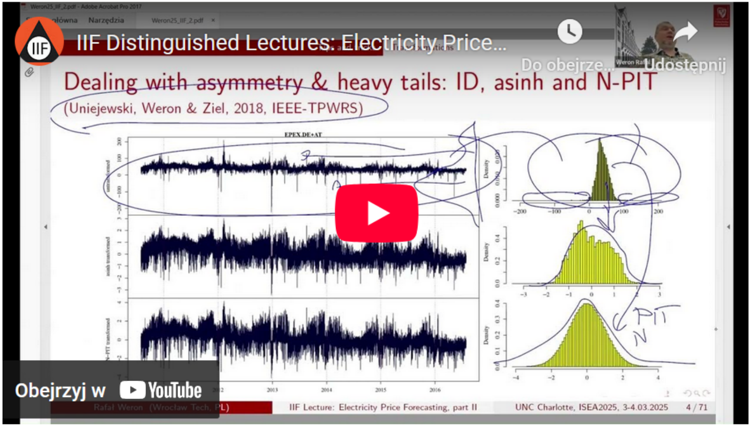
(Lipiecki, Uniejewski & Weron, 2024, ENEECO; illustrated here using EPEX-DE data)

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



What to learn more? See the IIF Distinguished Lectures

https://p.wz.pwr.edu.pl/∼weron.rafal/Conf/IIF24



Slides, snippets, movies: