Electricity price forecasting (in a nutshell)

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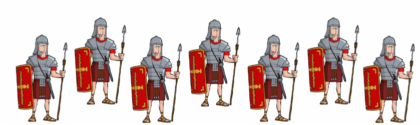
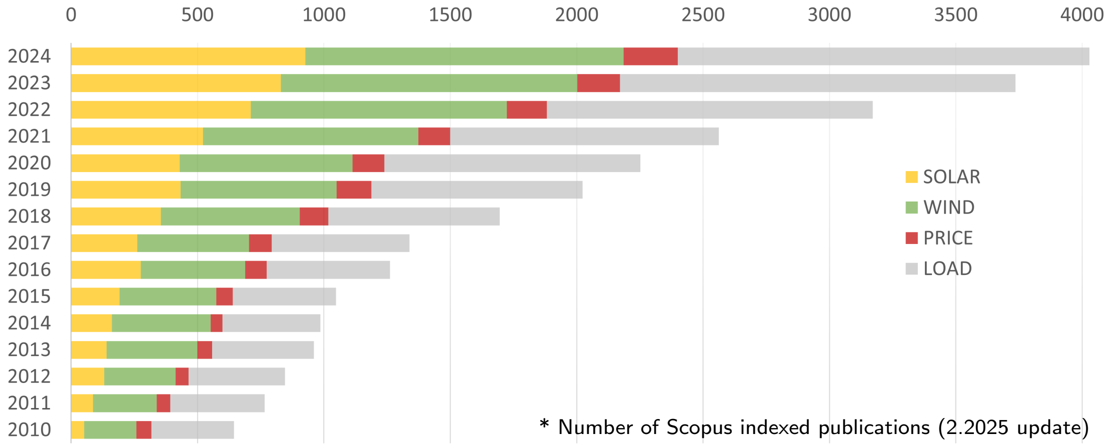
https://p.wz.pwr.edu.pl/∼weron.rafal

* 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), N.Kourentzes (U.Skövde), 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

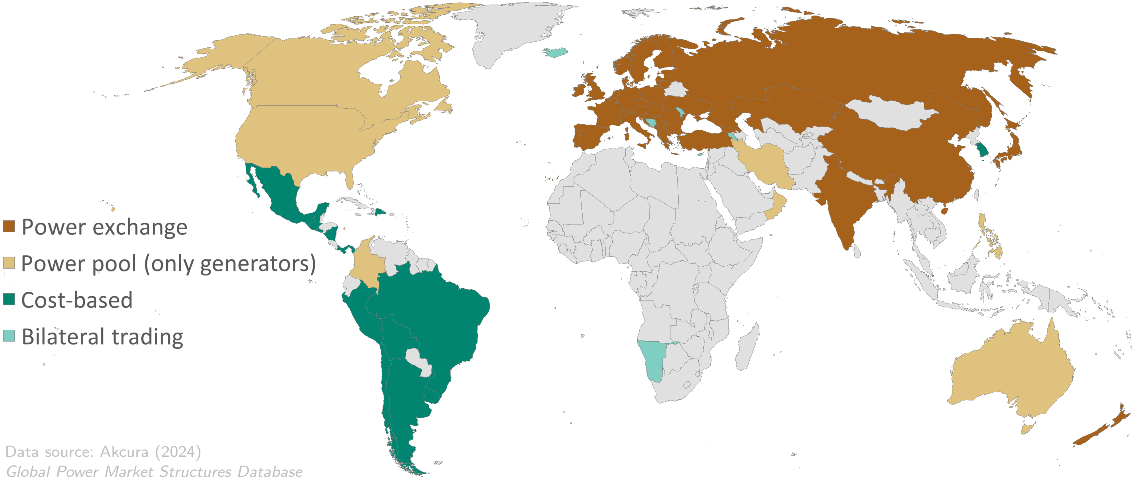
Energy (load, price, wind & solar) forecasting*

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



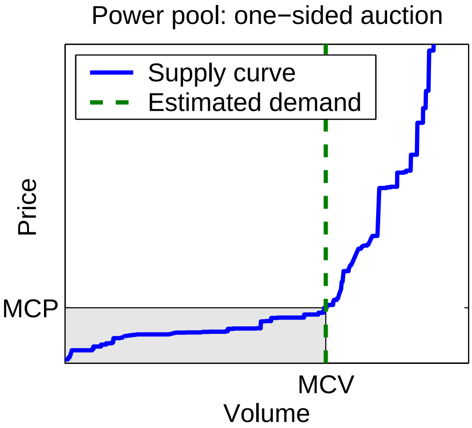
* Number of Scopus indexed publications (2.2025 update)

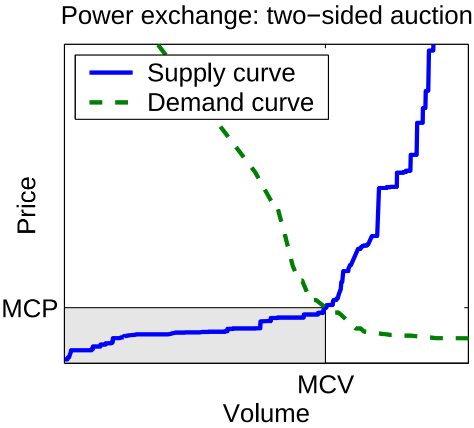
Competitive power market structures across the globe



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

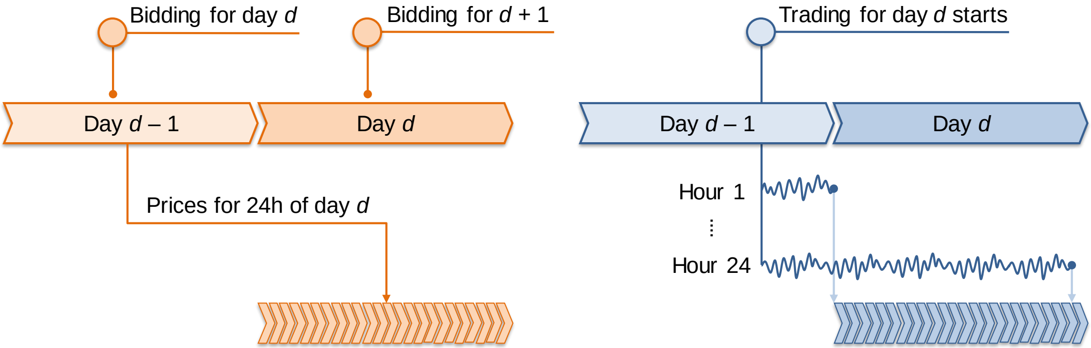
Power pool vs. power exchange





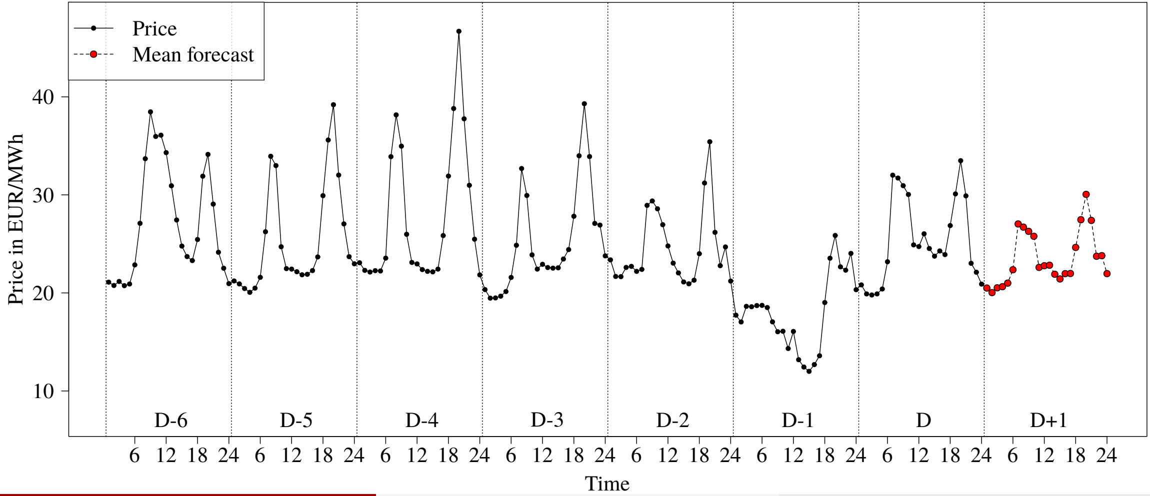
Day-ahead (> 90% of papers) vs. intraday (real-time) markets

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

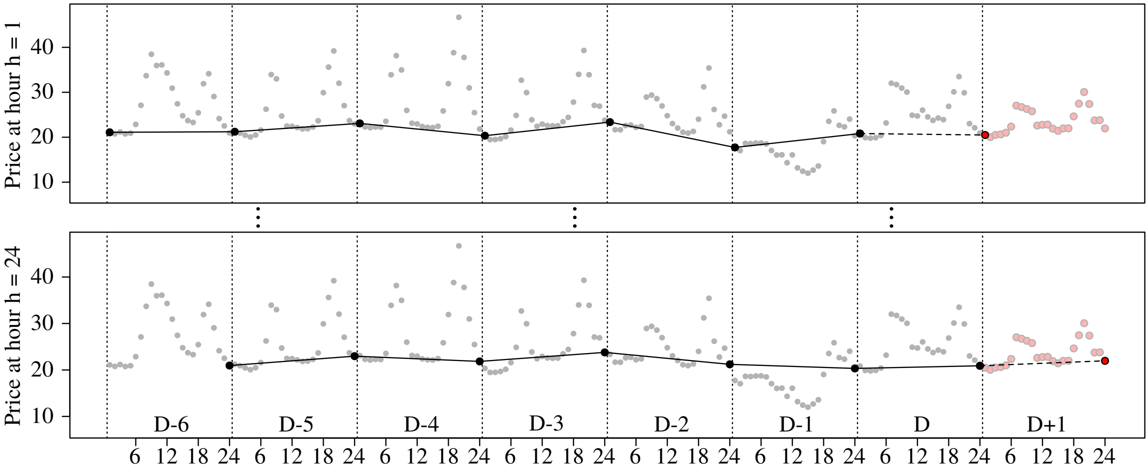


Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)

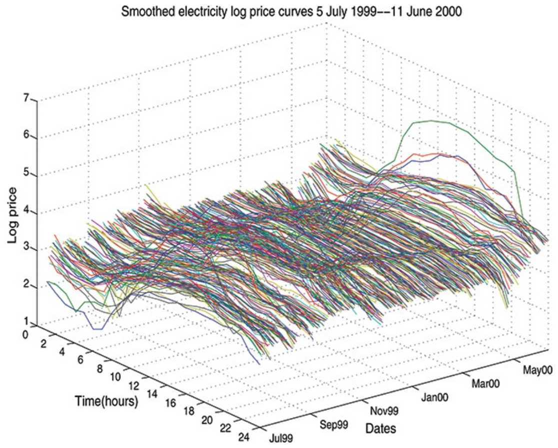


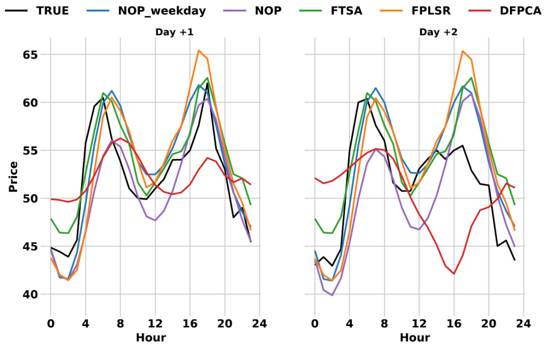
… multivariate …



... functional (data analysis) ...

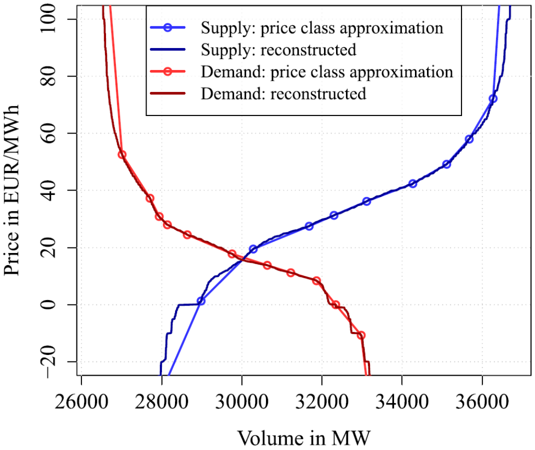
(Chen & Li, 2017, JBES; Chen et al., 2019, Ann.Appl.Stat; Wang & Cao, 2023, Environmetrics)

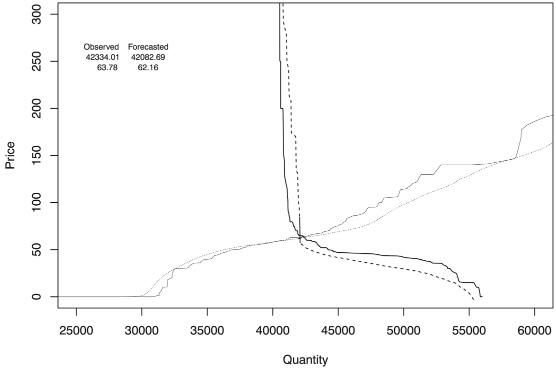




… or supply & demand curves?

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





What about mid- and long-term forecasts?

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

Autoregression | Futures (fuel, CO2) | Weekly dummies (+ seasonal RES/Load)

Model name	Week Dummies	Annual Seasons	Autoreg	RES & Load	Fuels	Unconstrained	Constrained	Current	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

Current – regress $P_{d,h}$ on RES/load (RL) and fuel/CO_2 prices (front-month futures), predict $\hat{P}_{d,h}$ using seasonal RES/Load and fuel/CO_2 futures

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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Journal of Cleaner Production

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

ELSEVIER

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

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

ABSTRACT

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.

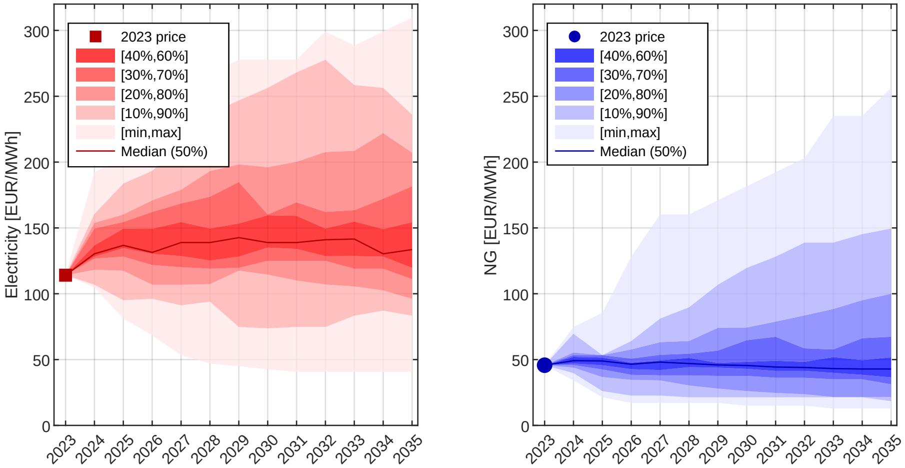
The circular economy not only promotes resource efficiency but also raises important social and environmental justice concerns. The current linear economy unequally distributes the environmental and social costs associated with energy and material provision, disproportionately affecting vulnerable groups 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)

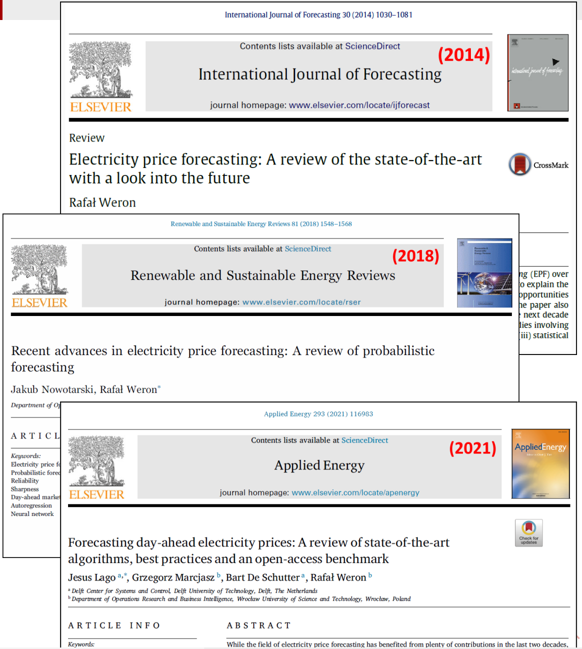


1 Introduction

2 Model evolution
- (Auto)regressive models
- Averaging across windows
- LASSO-Estimated AR (LEAR)
- Deep and interpretable ML
- Temporal Hierarchy Forecasting

3 Beyond point forecasts

4 Wrap-up


International Journal of Forecasting 30 (2014) 1030–1081

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International Journal of Forecasting

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ELSEVIER

Review

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

Rafał Weron

...ng (EPF) over ...o explain the ...pportunities ...he paper also ... next decade ...lies involving ...iii) statistical

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

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Renewable and Sustainable Energy Reviews

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ELSEVIER

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

Jakub Nowotarski, Rafał Weron*

Department of O...

ARTICL...

Keywords:
Electricity price f...
Probabilistic fore...
Reliability
Sharpness
Day-ahead marke...
Autoregression
Neural network

Applied Energy 293 (2021) 116983

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Applied Energy

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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:

ABSTRACT

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

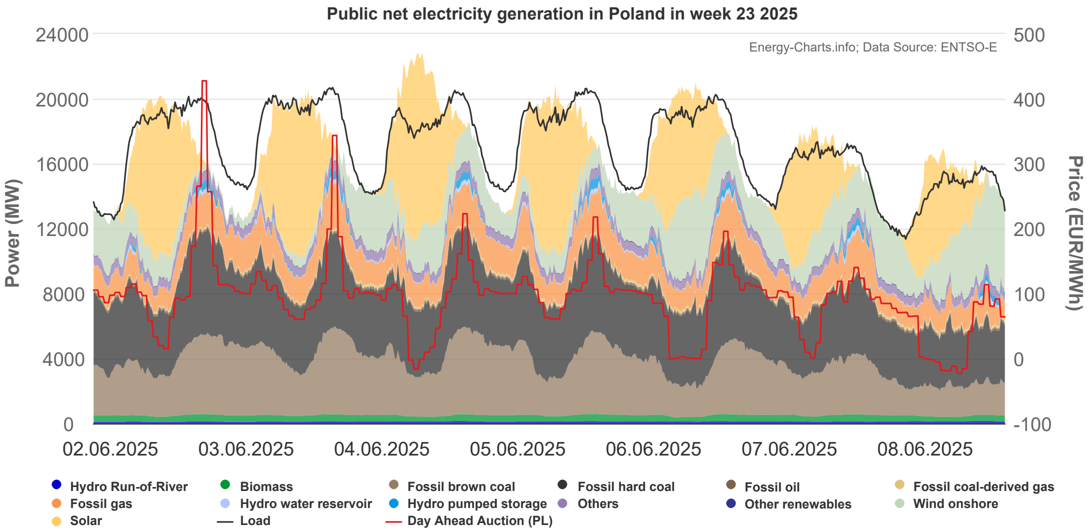
Expert ARX-type models

The workhorse of EPF – autoregressive structure with exogenous variables:

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

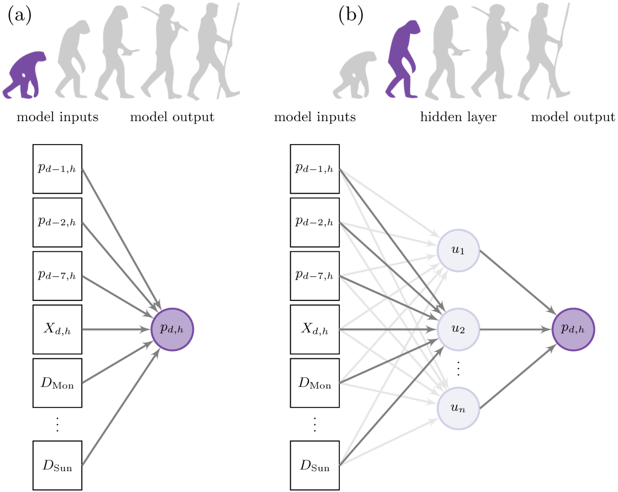
- Special cases:
  - Naive model $P^{(1)}_{d,h}$ for $\beta_1 = 1$ and $\beta_{i\neq 1} = 0$
  - AR(7), sparse AR(7) with some AR lags missing
  - ARX(7) with $K \geqslant 1$, sparse ARX(7) with some AR lags missing

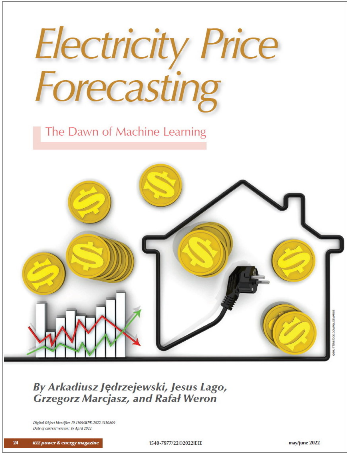
Do we need exogenous variables?



Linear regression (ARX) vs. shallow neural network (NARX)

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

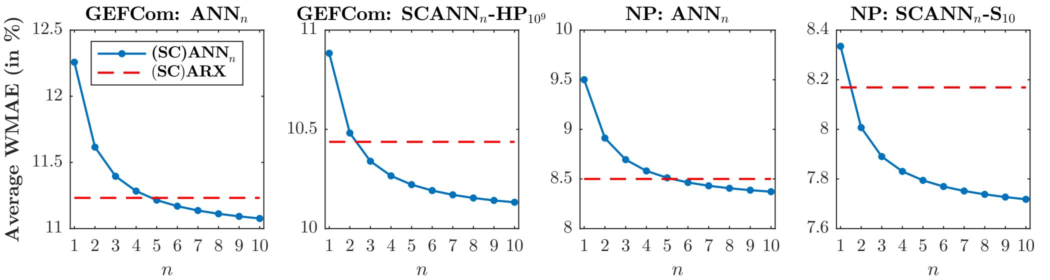




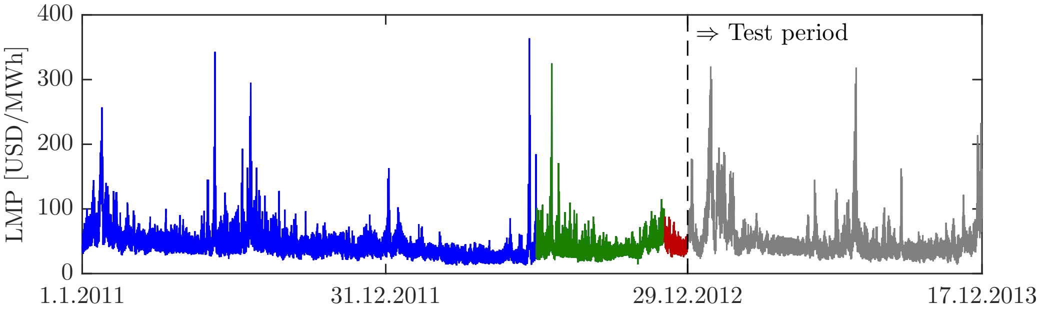
Committee machines: #runs vs. forecast accuracy

(Marcjasz, Uniejewski & Weron, 2019, IJF)

- The more runs ($\rightarrow$ longer computational time) the better
- The prediction error decays as a power law

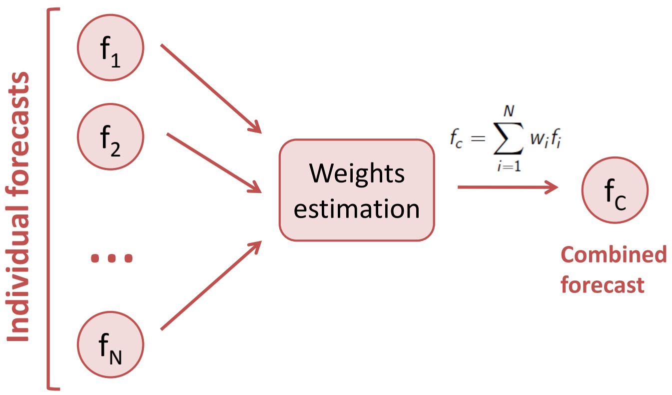


What is the optimal calibration (training) window size?



- 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

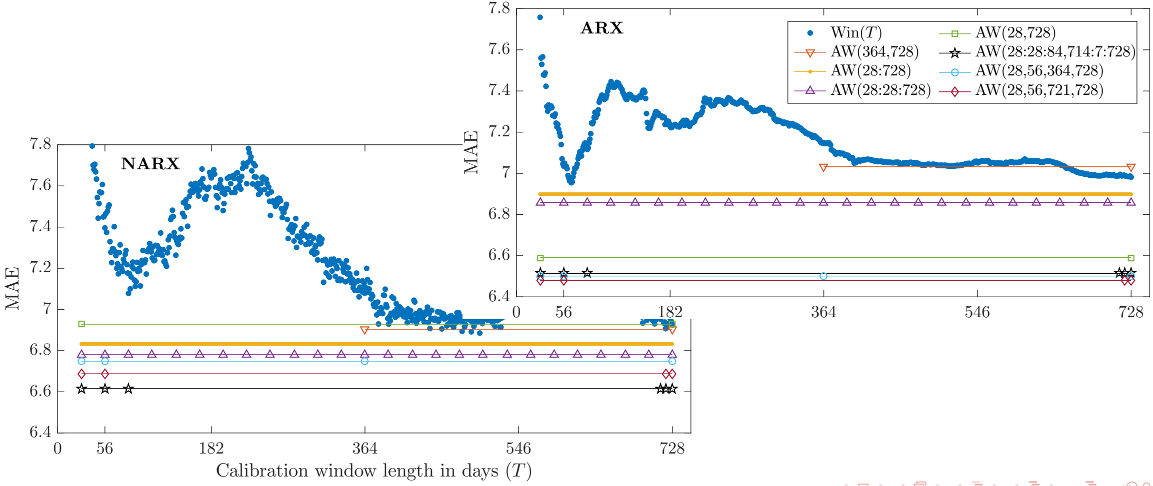
Point forecast averaging: The idea



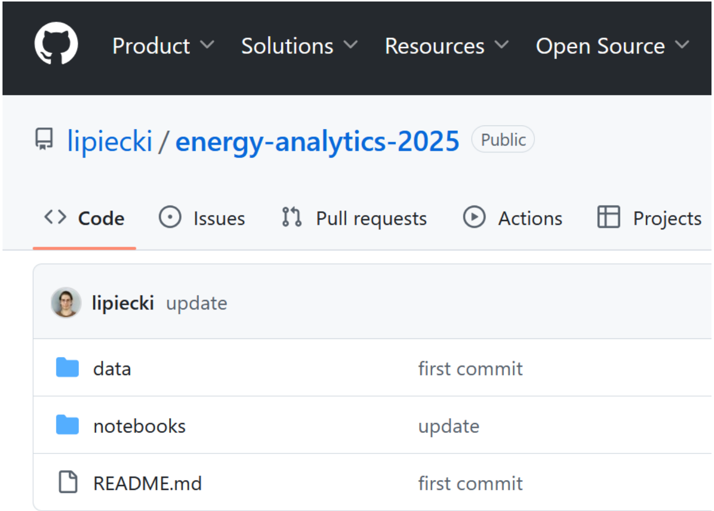
- Dates back to the works of Bates, Crane, Crotty & Granger (1960s)
- 'Statistical/Econometric world': *combining forecasts*, *forecast averaging* (not *model averaging*)
- 'AI/Engineering world': *committee machines*, *ensemble averaging*, *expert aggregation*

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)?

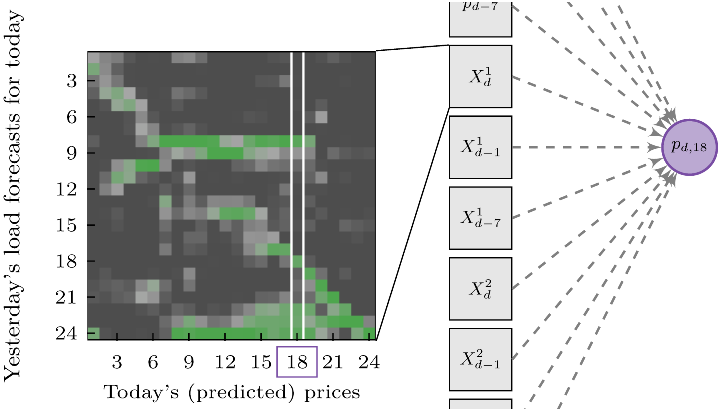
- Minimize the residual sum of squares (RSS $\equiv$ sum of squared errors) $+$ a penalty function of the betas:

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

  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

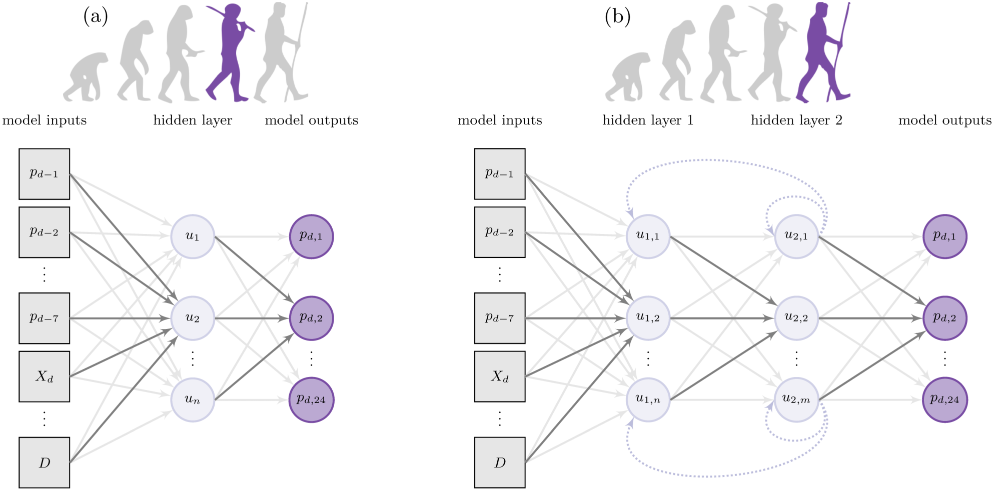
(Uniejewski et al., 2016; Ziel, 2016; Ziel & Weron, 2018; Jędrzejewski et al., 2022; Uniejewski, 2024)



Experiment yourself:

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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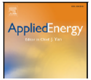

Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark

Jesus Lago [a,*], Grzegorz Marczjasz [b], Bart De Schutter [a], Rafał Weron [b]

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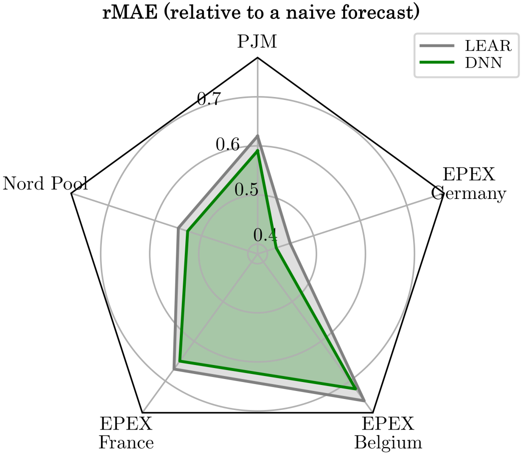
ARTICLE INFO

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

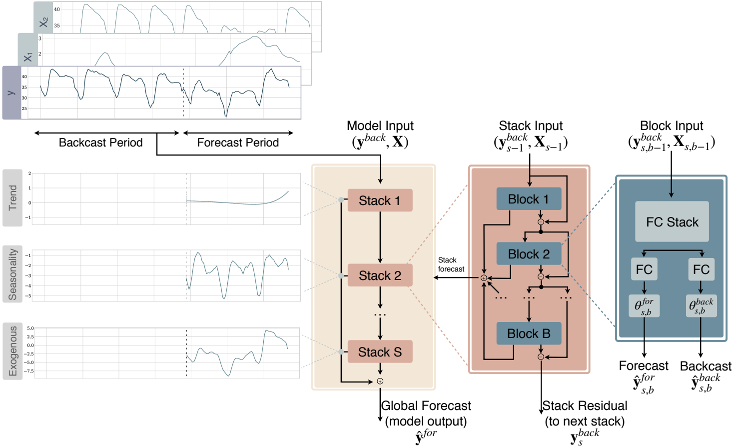
ABSTRACT

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.



Interpretable AI: NBEATSx

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



Experiment yourself:

Interpretable ML: What about performance?

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

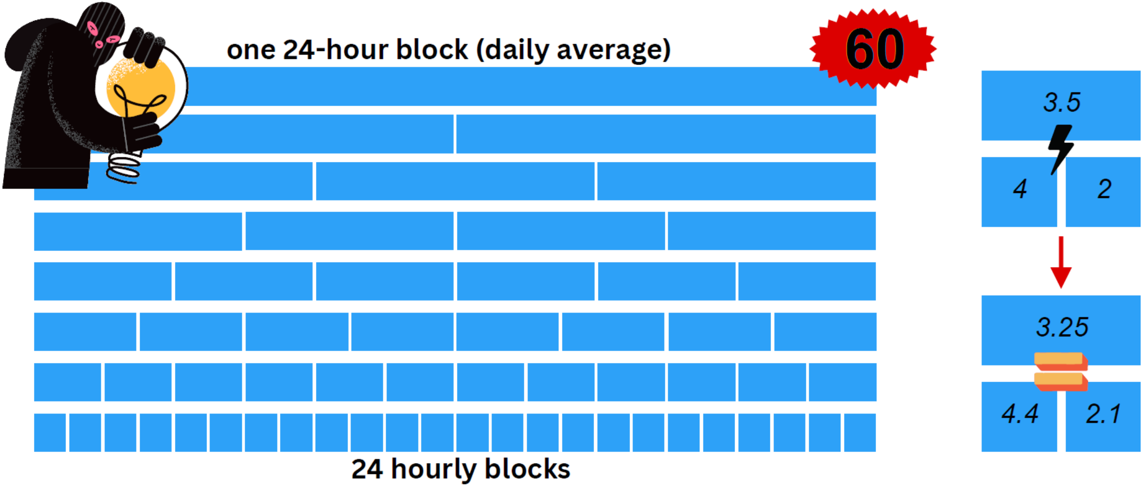
Tab. 3. Accuracy measures for day-ahead price forecasts (test sample of 2 years)

		ARx1	**LEARx**	**DNN**	**NBEATSx**
NP	MAE	2.01	1.74	1.68	1.62
	rMAE	0.63	0.55	0.53	0.51
	sMAPE	5.84	5.01	4.88	4.70
	RMSE	3.71	3.36	3.32	3.27
PJM	MAE	3.53	3.01	2.86	2.90
	rMAE	0.73	0.62	0.59	0.60
	sMAPE	13.64	11.98	11.33	11.61
	RMSE	5.74	5.13	5.04	4.84
EPEX-DE	MAE	4.36	3.61	3.41	3.29
	rMAE	0.54	0.45	0.42	0.41
	sMAPE	17.73	14.74	14.08	13.99
	RMSE	7.38	6.51	5.93	5.65
Daily recalibration [s]		—	18.57	50.65	81.61

LEARx, **DNN** – LEAR and DNN models from Lago et al. (2021, APEN), after Erratum
NBEATSx – NBEATSx-I (interpretable configuration) from Olivares et al. (2023, IJF)

Temporal Hierarchy Forecasting (THieF)

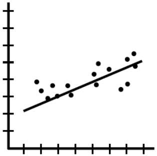
(Lipiecki, Bilińska, Kourentzes & Weron, 2025, arXiv)



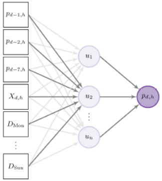
THiEF: Gains from reconciliation

(Lipiecki, Bilińska, Kourentzes & Weron, 2025, arXiv)

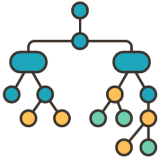
ARX



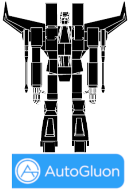
NARX



XGB



Mitra
72 million parameters



Level	Model	MAE	%gain	RMSE	%gain
1H	ARX	26.93	2.8%	39.83	2.7%
	NARX	23.06	3.3%	35.62	2.8%
	XGB	23.34	4.4%	37.05	5.5%
	Mitra	21.37	1.2%	33.31	1.2%
4H	ARX	25.65	3.1%	37.50	3.1%
	NARX	21.75	5.0%	33.27	4.6%
	XGB	22.01	5.8%	34.25	6.0%
	Mitra	20.13	3.7%	30.87	3.5%
8H	ARX	24.37	2.9%	35.59	3.5%
	NARX	20.54	5.5%	31.20	4.8%
	XGB	21.07	6.8%	32.94	8.2%
	Mitra	19.45	6.3%	29.34	5.5%
24H	ARX	20.92	2.0%	30.29	3.4%
	NARX	17.99	8.2%	27.24	7.9%
	XGB	18.80	11.7%	29.50	13.4%
	Mitra	16.56	8.1%	24.81	8.5%

1 Introduction

2 Model evolution

3 Beyond point forecasts
- Do we need probabilistic forecasts?
- Postprocessing point forecasts
- Combining probabilistic forecasts
- Distributional Deep Neural Nets

4 Wrap-up

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Review

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

Jakub Nowotarski, Rafał Weron*
Department of O

ARTICL

Keywords:
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Probabilistic fore
Reliability
Sharpness
Day-ahead marke
Autoregression
Neural network

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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
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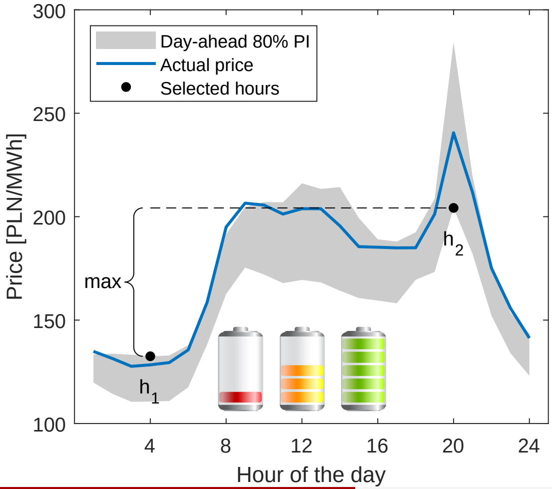
ABSTRACT

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

Do we need probabilistic (interval, density) forecasts?

(Uniejewski & Weron, 2021, ENEECO)



Quantile-based trading strategy

Simultaneously bid day-ahead:

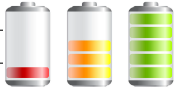
- buy 1 MW for $\hat{P}^{1-\alpha}_{d,h_1}$ at hour h_1
- sell 0.8 MW at $\hat{P}^{\alpha}_{d,h_2}$ at hour h_2

$\leftarrow$ 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)

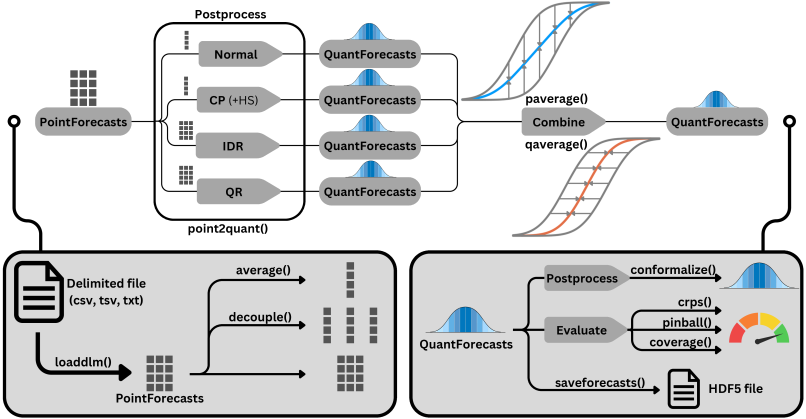


Strategy			**Profit**		
Naive (4am–12pm)			33 065.29		
Point forecasts-based			33 722.39		
Quantile-based	1-99%	5-95%	10-90%	20-80%	25-75%
Q-Ave	41 317.92	43 328.89	43 432.31	43 289.09	43 033.88
F-Ave	39 848.26	43 369.44	44 052.04	44 088.11	43 130.34
QRM	41 163.29	43 054.28	43 124.12	43 731.54	42 240.25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

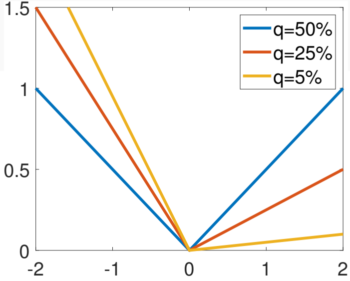


Experiment yourself:

Quantile Regression Averaging (QRA)

(Nowotarski & Weron, 2015, COST)

Pinball loss (average over $q \to$ CRPS)



Individual point forecasts

$\hat{Y}_{1,t}$

$\hat{Y}_{2,t}$

$\vdots$

$\hat{Y}_{m,t}$

Quantile regression:

$$\min_{\boldsymbol{\beta}_q} \left[\sum_t \left(q - 1_{Y_t < \boldsymbol{X}_t \boldsymbol{\beta}_q} \right) \left(Y_t - \boldsymbol{X}_t \boldsymbol{\beta}_q \right) \right]$$

$$\boldsymbol{X}_t = \left[1, \hat{Y}_{1,t}, \dots, \hat{Y}_{m,t} \right]$$

$\boldsymbol{\beta}_q$ - vector of parameters

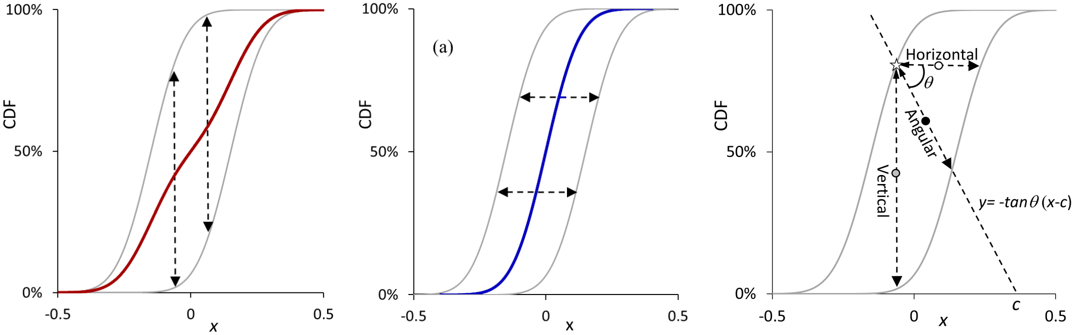
$$\left[\hat{Y}_t^L, \hat{Y}_t^U \right]$$

Combined interval forecast, e.g., for $q = 0.05$ & 0.95

Combining probabilistic forecasts is tricky ...

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

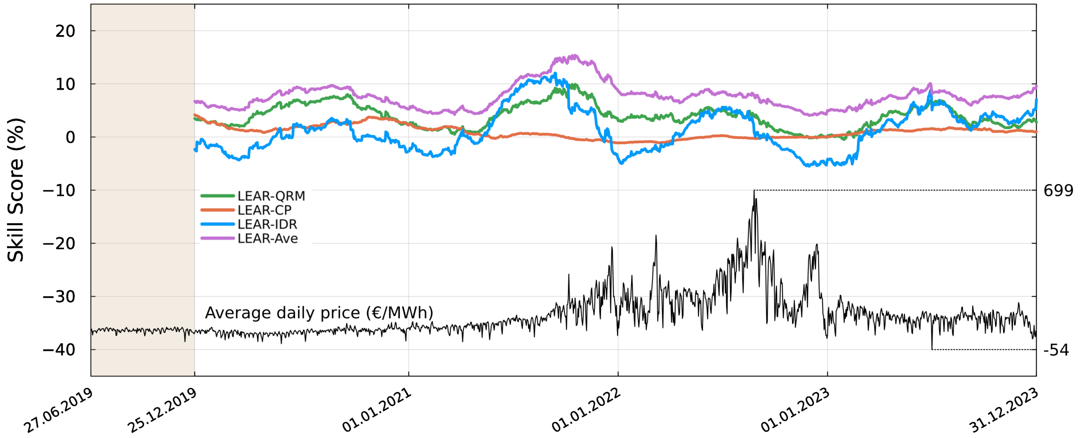
Vertical (over probabilities), **horizontal** (quantiles → sharper CDF) ... or at any angle



... but can be beneficial

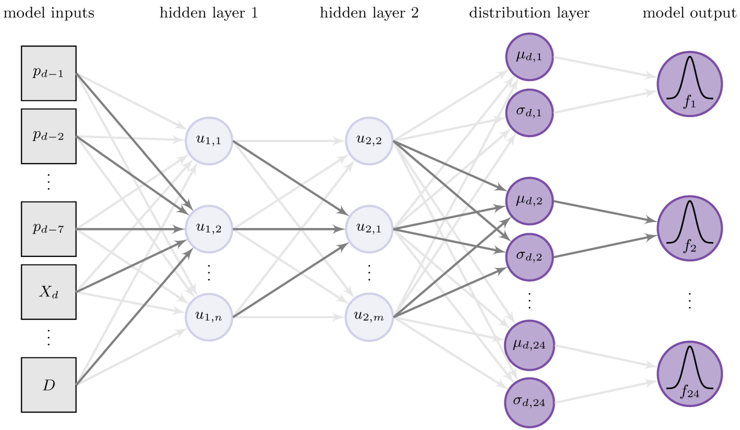
(Lipiecki, Uniejewski & Weron, 2024, ENEECO; illustrated here using EPEX-DE data)

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) perform well ...

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

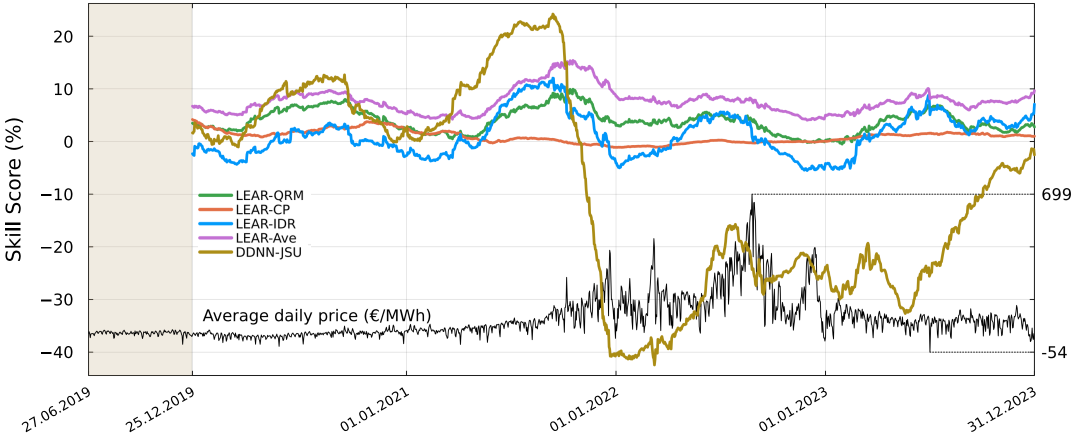


Experiment yourself:

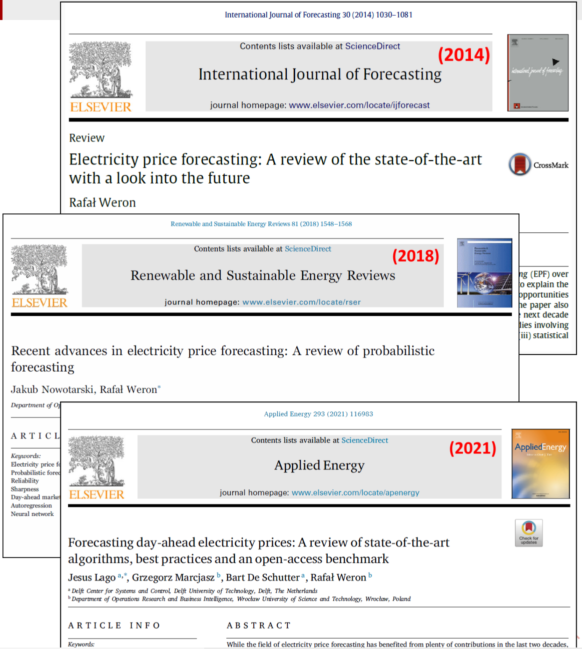
… but can fail miserably during volatile periods

(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



1. Introduction
   - Power markets across the globe
   - Model taxonomy
2. Model evolution
   - (Auto)regressive models
   - Averaging across windows
   - LASSO-Estimated AR (LEAR)
   - Deep and interpretable ML
   - Temporal Hierarchy Forecasting
3. Beyond point forecasts
   - Do we need probabilistic forecasts?
   - Postprocessing point forecasts
   - Combining probabilistic forecasts
   - Distributional Deep Neural Nets
4. Wrap-up



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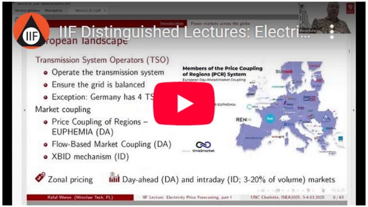
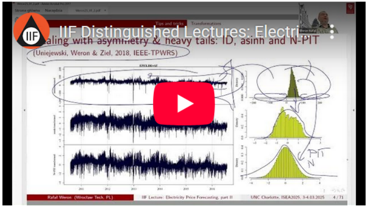
What to learn more? See the IIF Distinguished Lectures

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

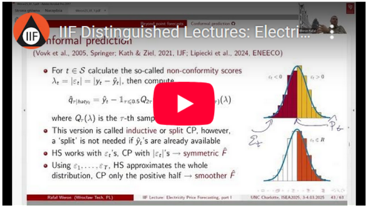
Part I, Lecture I



Part II, Lecture I



Part I, Lecture II



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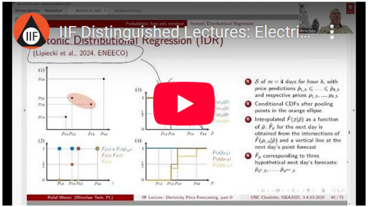

Slides, snippets, movies: