

Electricity price forecasting in the 2020s (MMXXs)

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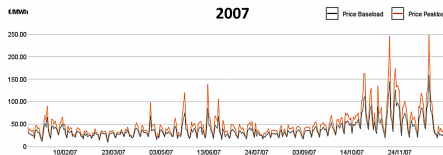
*Based on joint work with K.Hubicka, A.Jędrzejewski, K.Maciejowska, G.Marcjasz, J.Nasiadka, W.Nitka, T.Serafin, B.Uniejewski (PWr), J.Lago (Amazon), J.Nowotarski (BNY Mellon), C.Kath, M.Narajewski, F.Ziel (Essen), C.Challu, K.Olivares (Carnegie Mellon)

THE WORLD IS CHANGING ...



The power markets are changing ...

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

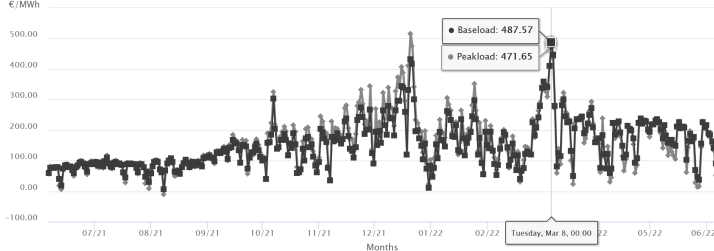


Price

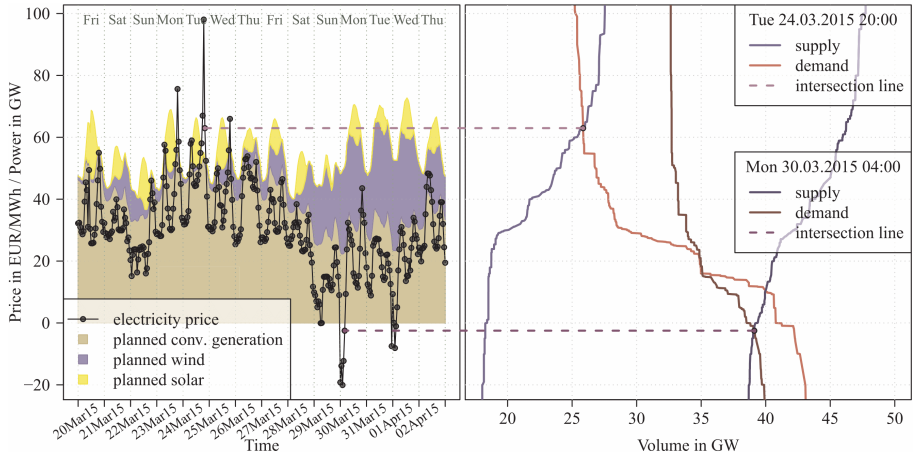
€/MWh

June 2021 - June 2022

Auction > Day-Ahead > 60min > DE-LU



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

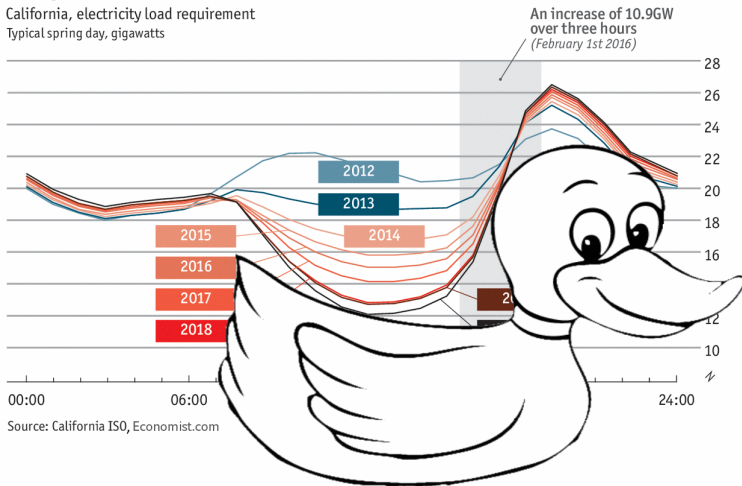


Source: Ziel & Steinert (2018, RSER)

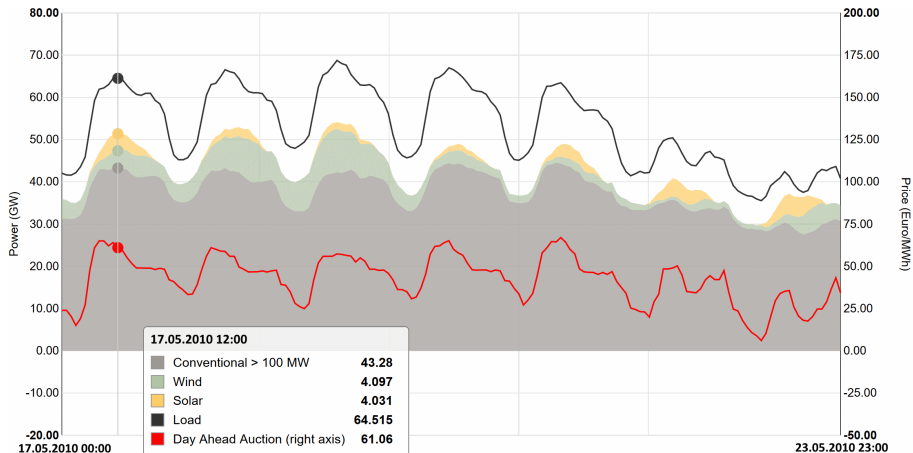
... and solar penetration

Who gets the bill?

California, electricity load requirement
Typical spring day, gigawatts

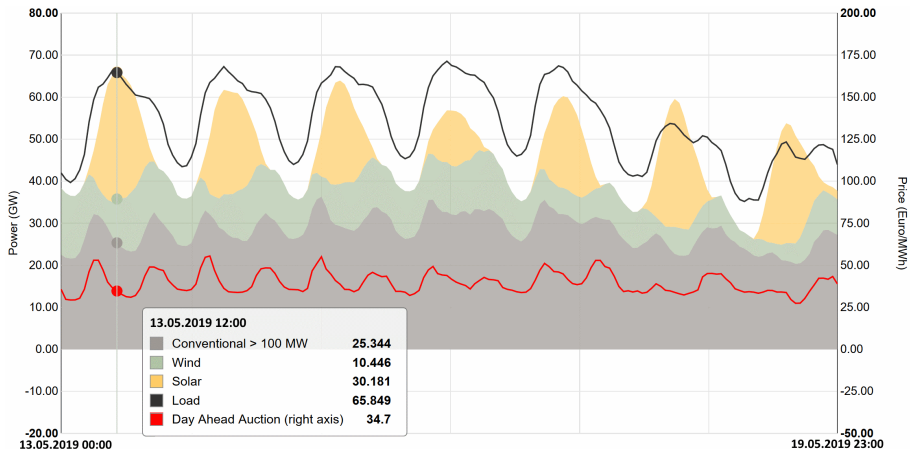


Germany 2010: No ducks



Source: www.energy-charts.de

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



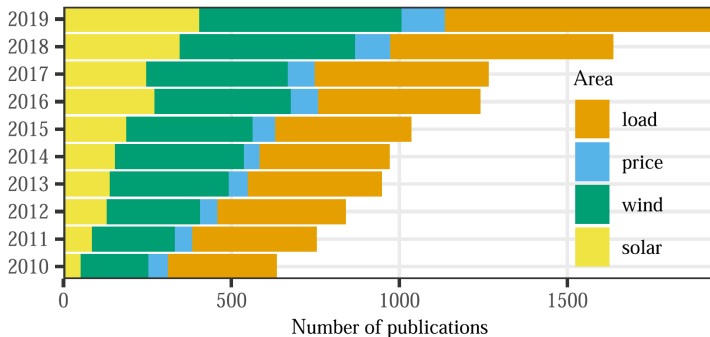
Source: www.energy-charts.de

But the (Academic) Empire ...



Load, price, wind & solar forecasting*

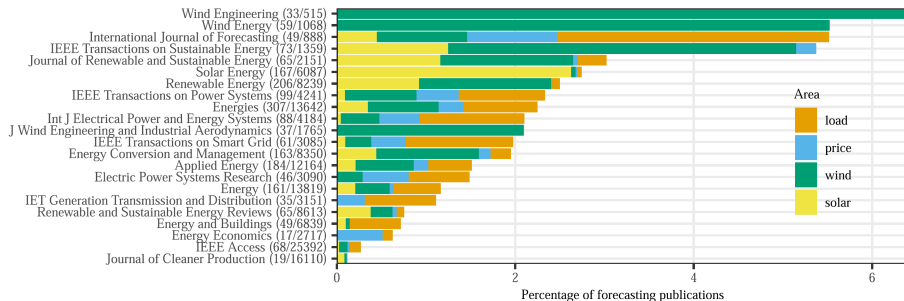
(Hong, Pinson, Wang, Weron, Yang & Zareipour, 2020, IEEE OAJPE)



* Scopus indexed

Percentage of energy forecasting publications*

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

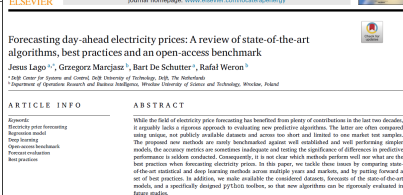
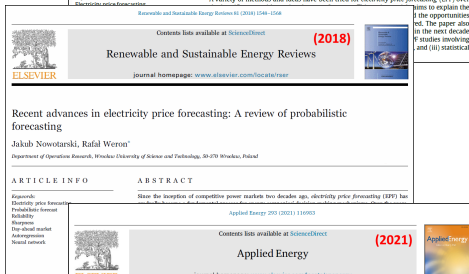


* Top 10 journals in each area (2010-2019); some are ranked top 10 across multiple areas

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

Agenda

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



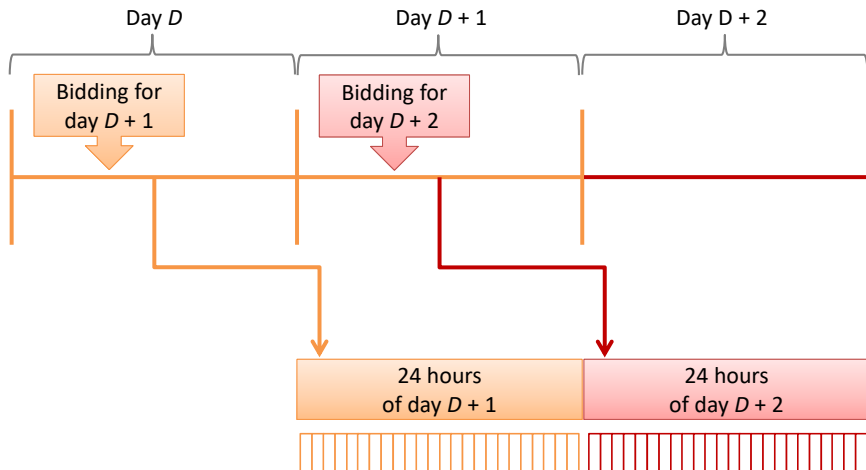
Why forecast electricity spot prices?

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



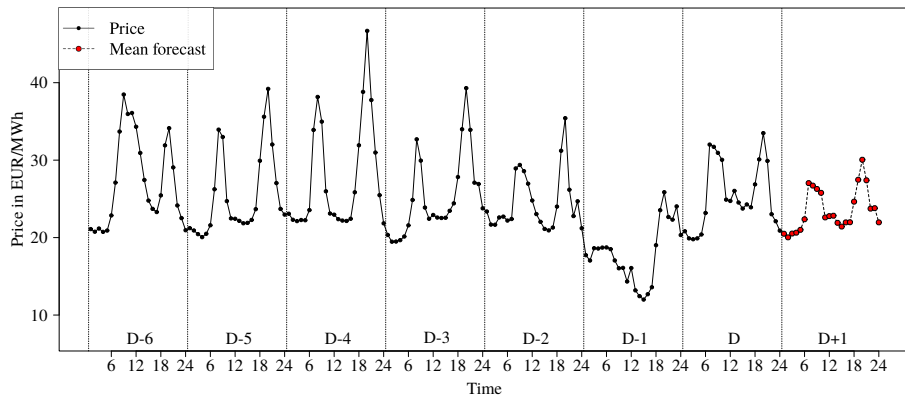
The workhorse of European power trading

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

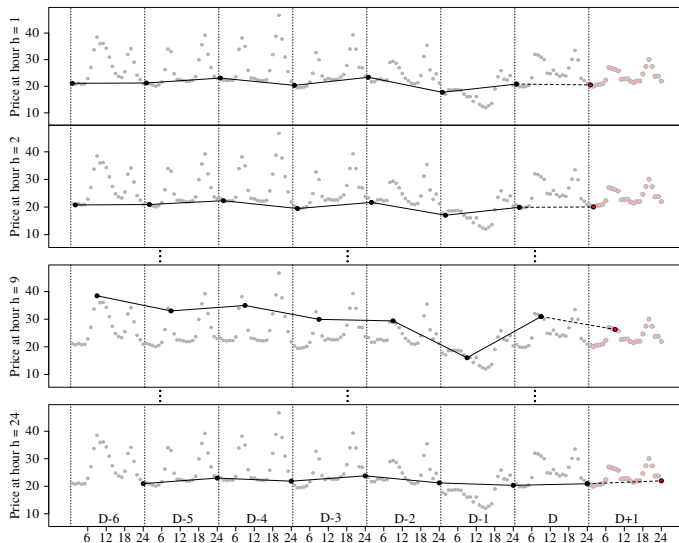


Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)



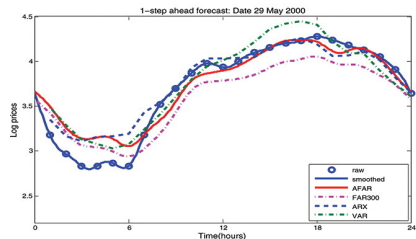
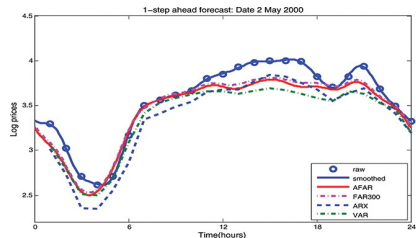
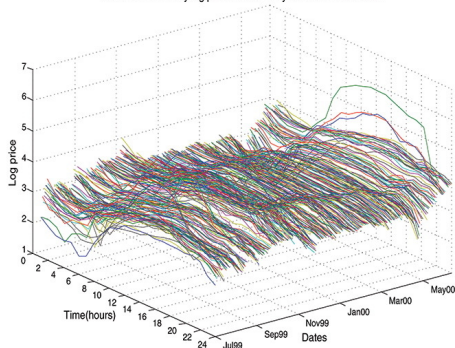
... multivariate ...



... or functional (data analysis)?

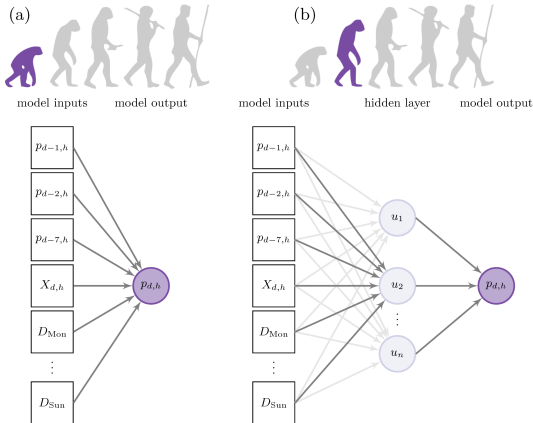
(Chen & Li, 2017, JBES; Chen et al., 2019, Ann.Appl.Stat.)

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



Which modeling framework?

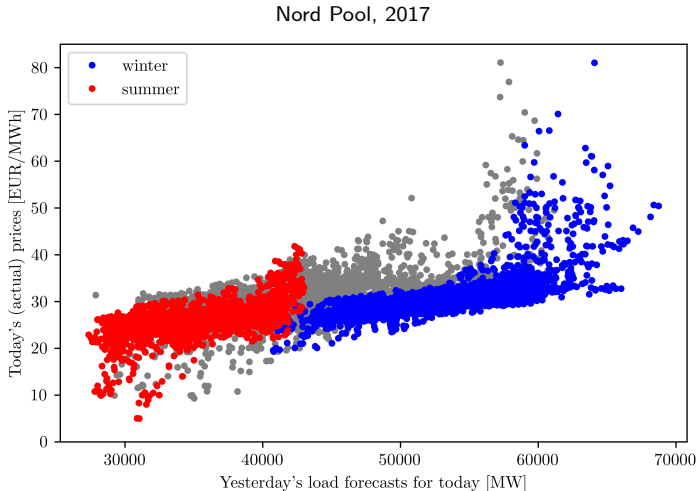
(Jędrzejewski, Lago, Marcjasz & Weron, 2022, IEEE-PEM)



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

Why nonlinear?

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

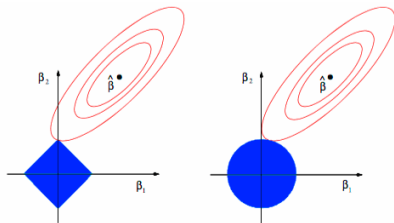


LASSO-Estimated AR (LEAR)

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

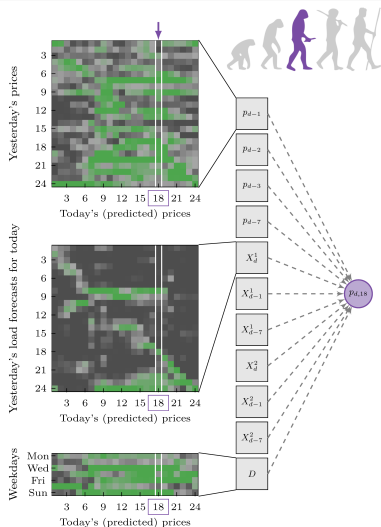
Minimize the residual sum of squares (RSS) + a penalty:

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



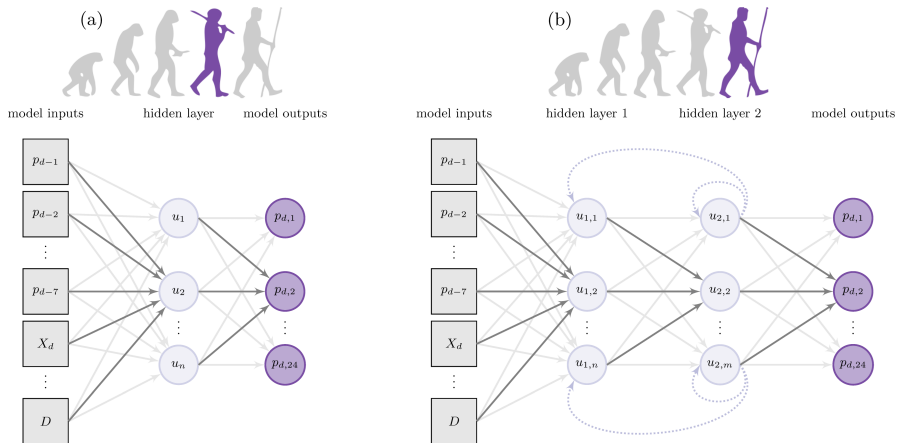
Blue areas – constraint regions, e.g., $|\beta_1| + |\beta_2| \leq t$

Red ellipses – contours of the LS error function



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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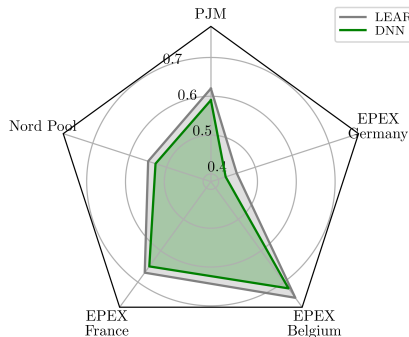
Keywords:

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

ABSTRACT

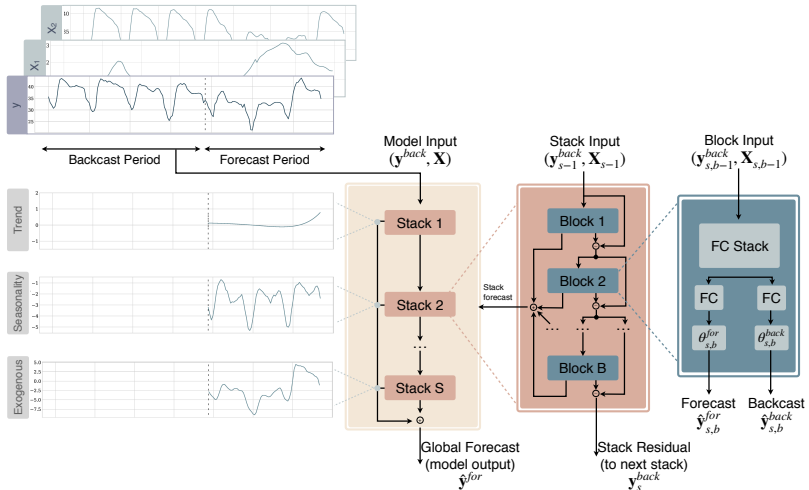
While the field of electricity price forecasting has benefited from it arguably lacks a rigorous approach to evaluating new prediction using unique, not publicly available datasets and across too short time horizons. The proposed new methods are rarely benchmarked against well-established models, the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

rMAE (relative to a naive forecast)



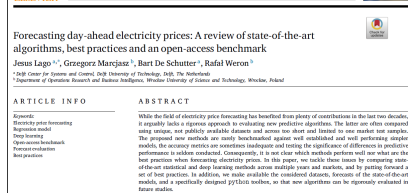
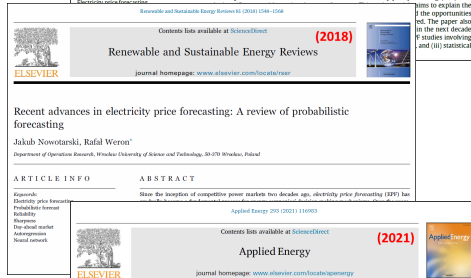
Interpretable NNs: NBEATSx

(Olivares, Challu, Marcjasz, Weron & Dubrawski, 2022, IJF)

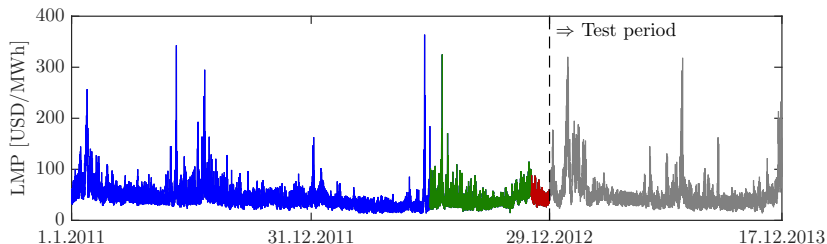


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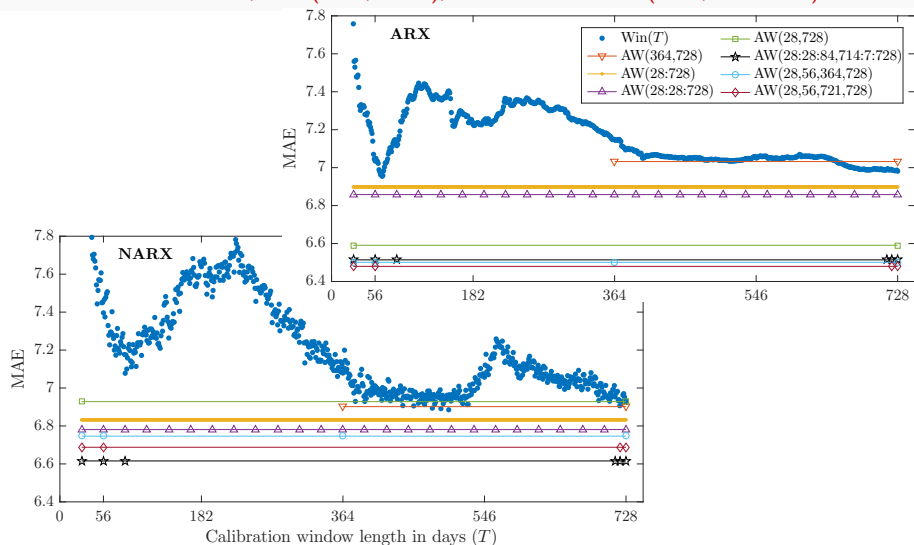
Searching for the optimal calibration window



- 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

Averaging across calibration windows

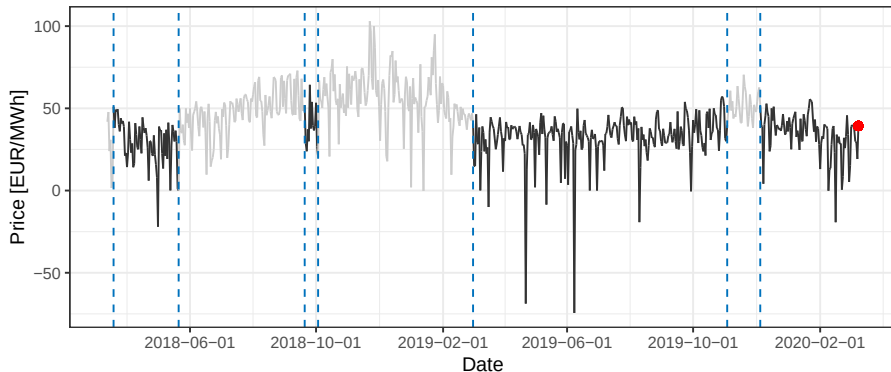
Structural breaks: Pesaran, Pick (2011, JBES); EPF: Hubicka et al. (2019, IEEE-TSE)



Detection of change/breakpoints

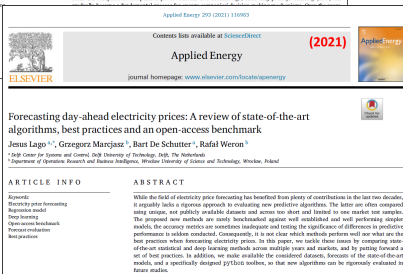
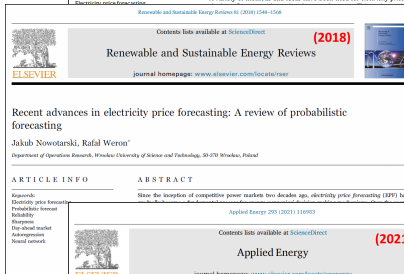
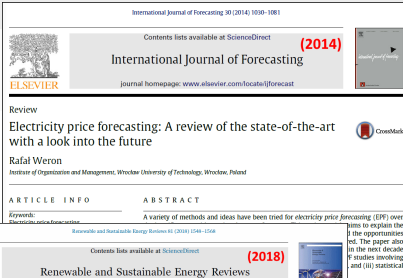
(de Marcos, Bunn, Bello & Reneses, 2020, *Energies*; Nasiadka, Nitka & Weron, ICCS 2022)

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



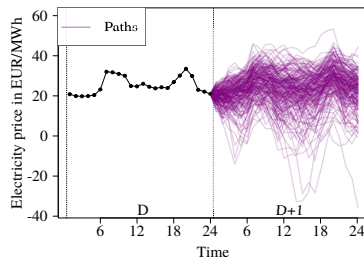
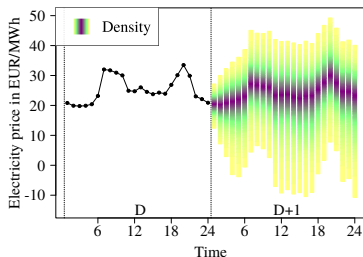
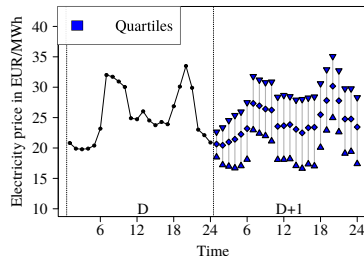
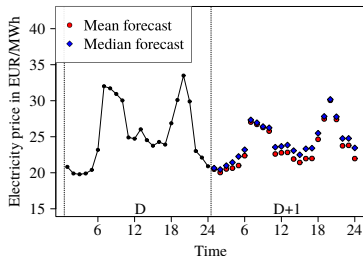
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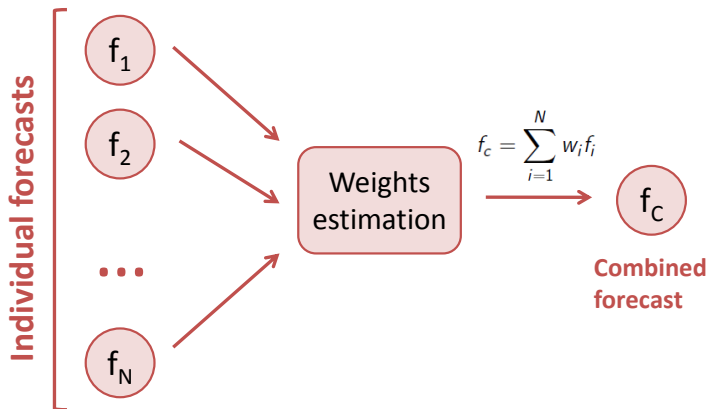


Point $\rightarrow$ probabilistic $\rightarrow$ path forecasting

(< 10% of EPF papers)



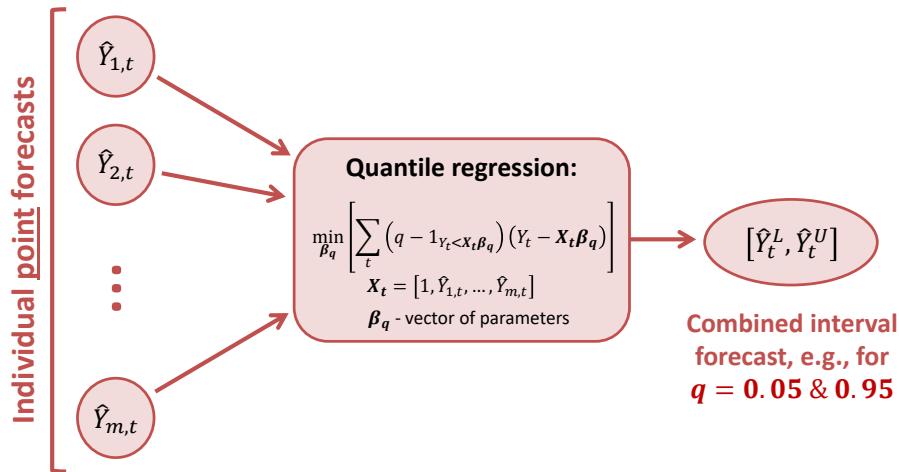
Point forecast averaging: The idea



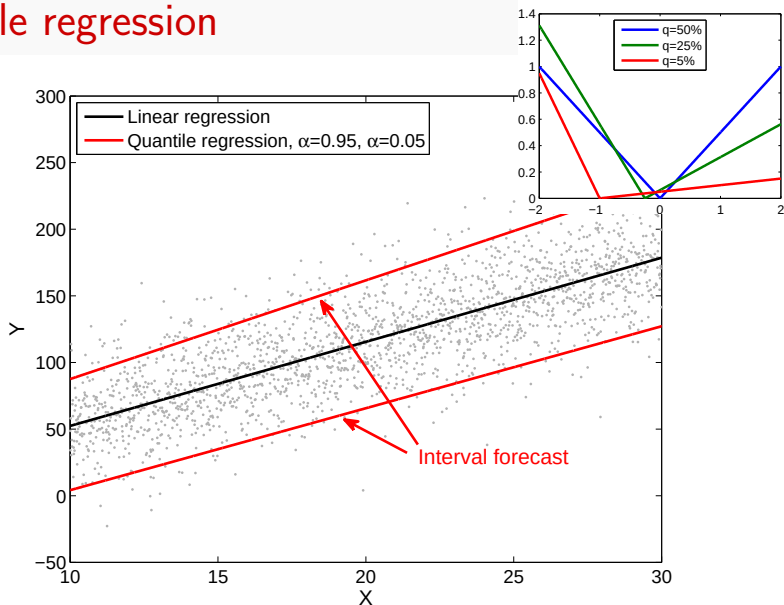
- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger

Quantile Regression Averaging: The idea

(Nowotarski & Weron, 2015, COST)

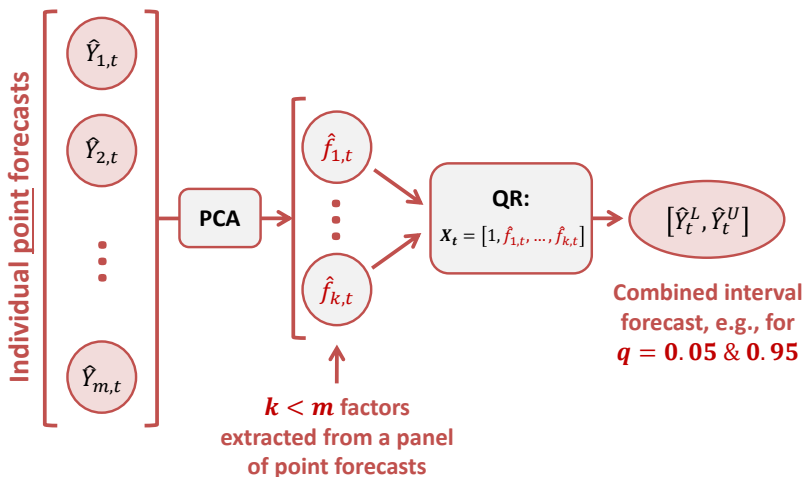


Quantile regression



FQRA: When the number of predictors is large

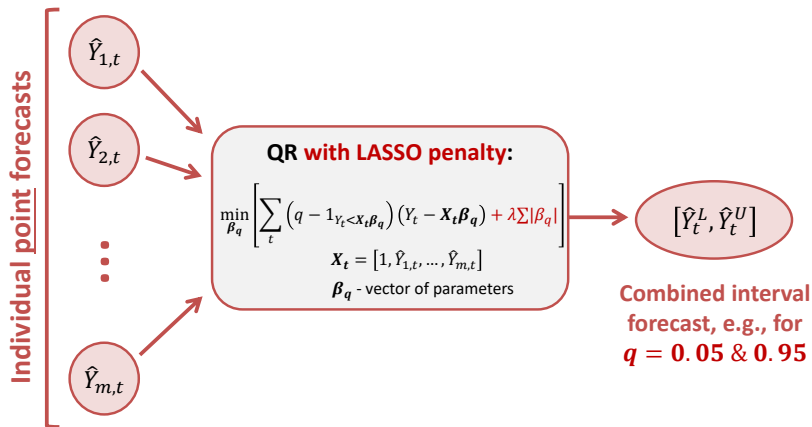
(Maciejowska, Nowotarski & Weron, 2016, IJF)



LQRA: When the number of predictors is large

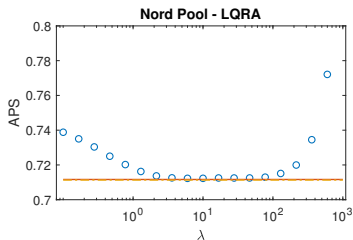
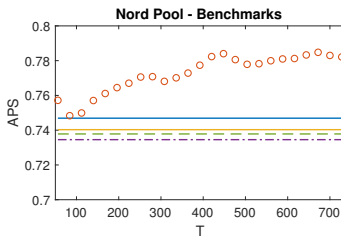
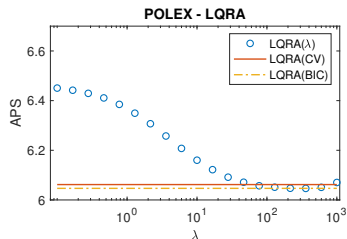
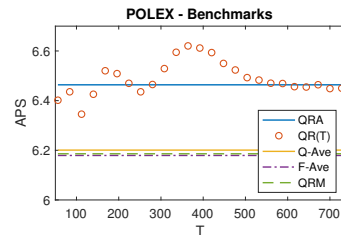
(Uniejewski & Weron, 2021, ENEECO)

~ 5% improvement over QRA



LQRA: Aggregate Pinball Scores (APS)*

(Uniejewski & Weron, 2021, ENEECO)

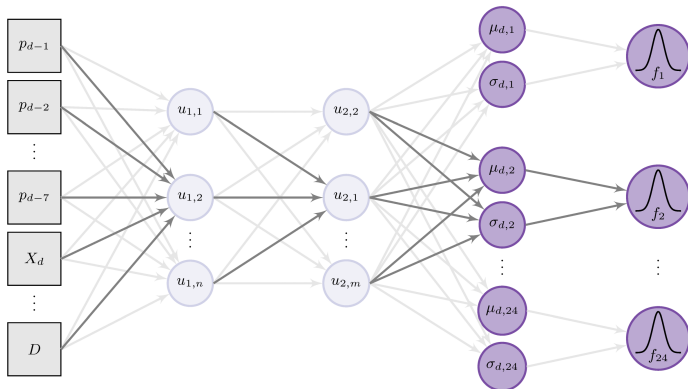


*Arithmetic averages over 99 percentiles and all hours in the test period

Probabilistic neural nets

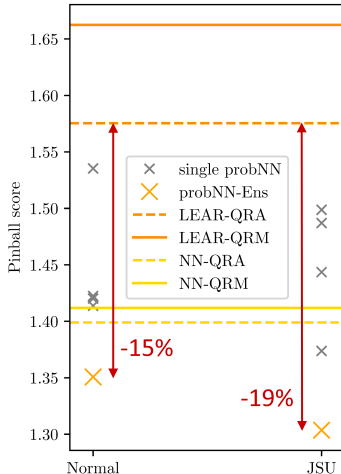
(Jędrzejewski et al., 2022, IEEE-PEM; Marcjasz, Narajewski, Weron & Ziel, 2022, WP)

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

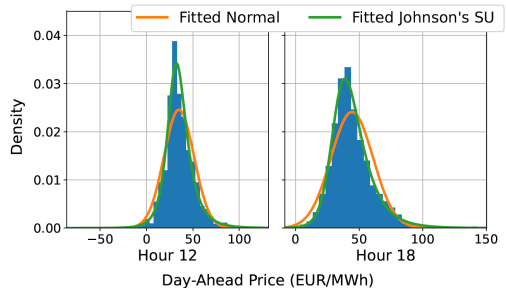


Perform surprisingly well ... after averaging

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

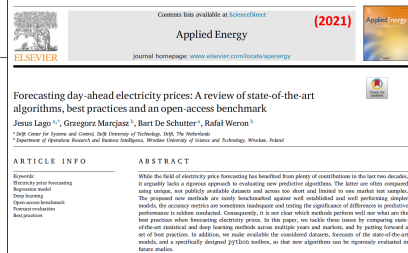
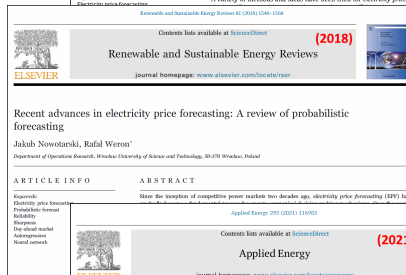


	MAE	RMSE	pinball
Naive	9.336	14.378	3.585
LEAR-QRA	4.161	6.699	1.575
LEAR-QRM	4.285	6.782	1.662
NN-QRA	3.668	5.830	1.399
NN-QRM	3.670	5.822	1.412
probNN-Ens N	3.663	5.969	1.351
probNN-Ens JSU	3.542	5.741	1.304



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



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(2020)



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Przemysław Zaleski ^{3,5} and Rafał Weron ^{3,*}

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

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

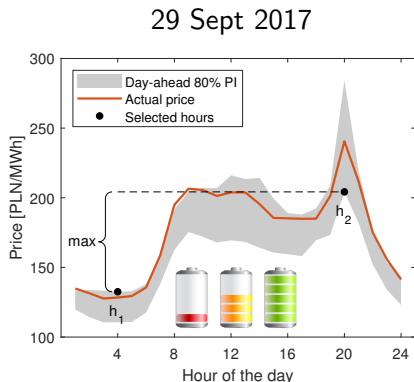
tomek.weron@email.com (TW); przemyslaw.zaleski@nwt.edu.pl (PZ)

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

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Quantile-based trading strategies

(Uniejewski & Weron, 2021, ENEECO)



Simultaneously bid day-ahead:

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

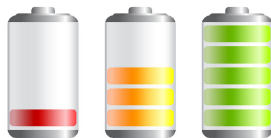
← With $\alpha = 10\%$ the spread is maximized for $\hat{P}_{d,4}^{90\%} = 133$ and $\hat{P}_{d,20}^{10\%} = 204$ PLN/MWh

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

Quantile-based trading strategies: Results

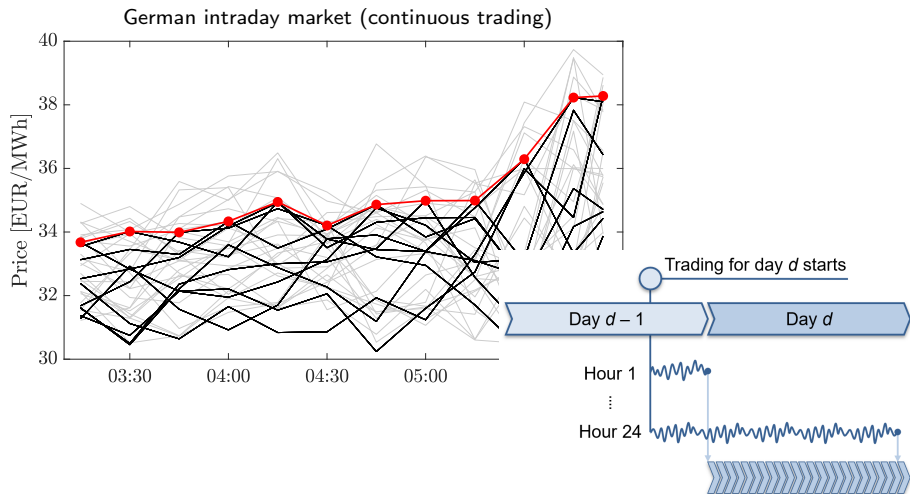
(Uniejewski & Weron, 2021, ENEECO)

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



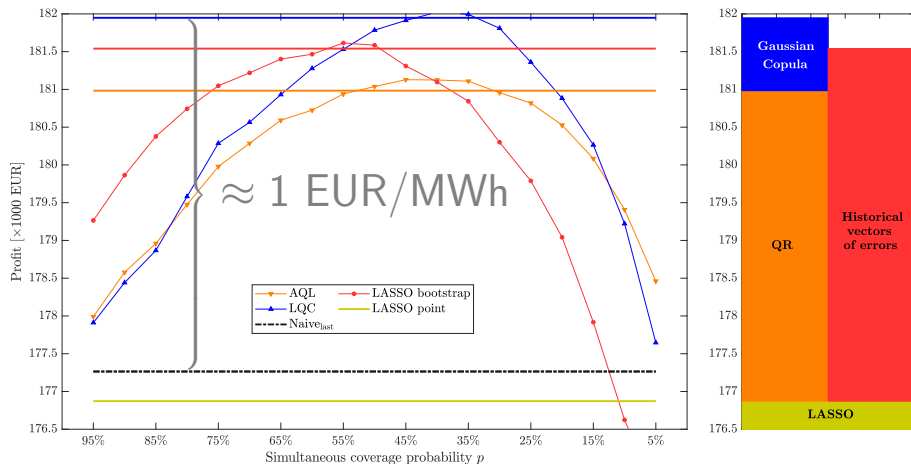
Prediction bands-based trading strategies

(Serafin, Marcjasz & Weron, 2021, WP)



Profits: Selling 1 MW every hour for 200 days

(Serafin, Marcjasz & Weron, 2021, WP)



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