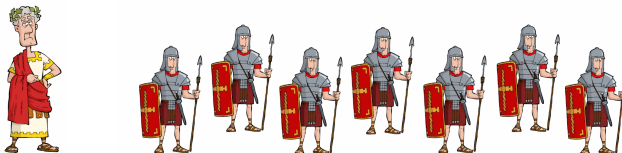


Recent advances in electricity price forecasting: A MMXIX (i.e., 2019) perspective

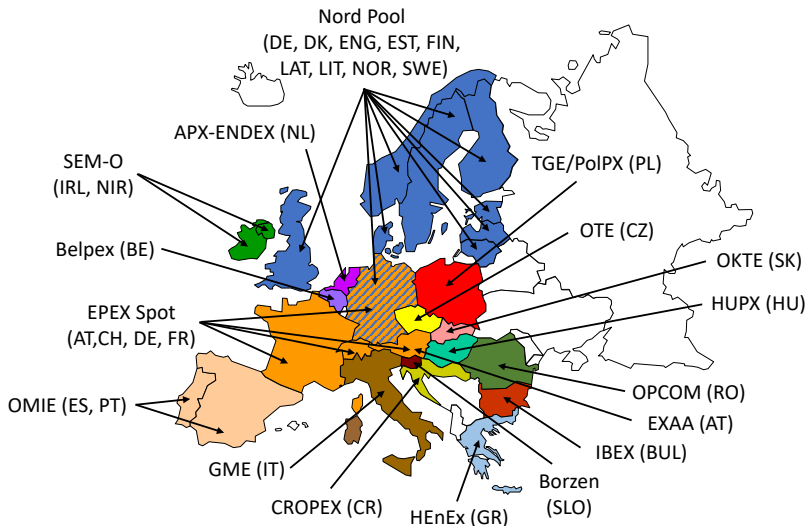
Rafał Weron*

Department of Operations Research
Wrocław University of Science and Technology (PWr), Poland
<http://kbo.pwr.edu.pl/en/staff/rafal-weron/>



*Based on work with K.Hubicka, K.Maciejowska, G.Marcjasz, W.Nitka, T.Serafin, B.Uniejewski, T.Weron, P.Zaleski (PWr)
J.Nowotarski (BNY Mellon), M.Zator (Kellogg), C.Kath, F.Ziel (Essen)

Markets for electricity in Europe ...

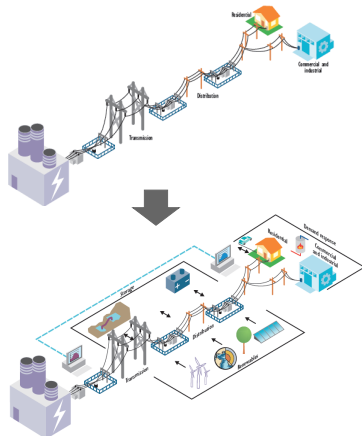
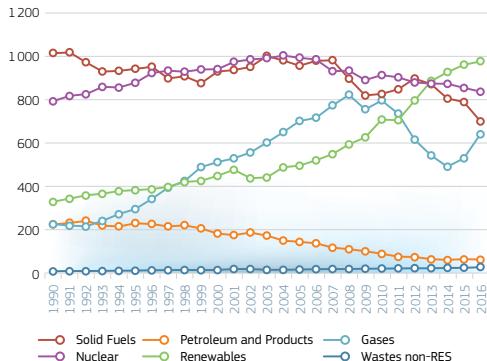


... are undergoing a transformation ...

The resource mix transitions from fossil fuels to renewables

2.6.2 Gross Electricity Generation

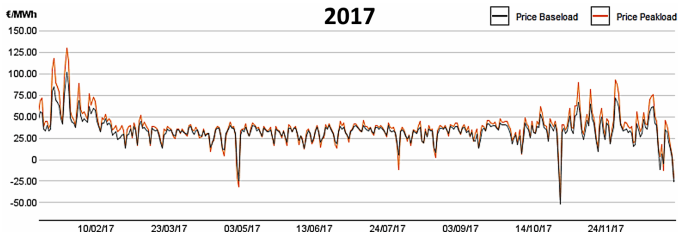
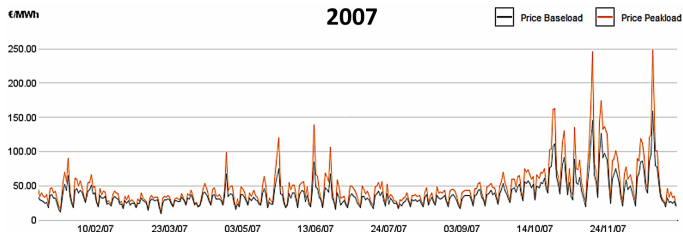
BY FUEL – EU-28 – ALL FUELS – 1990-2016 (TWh)



Sources: EU (2018), Adigbli (2017)

... and the price characteristics are changing ...

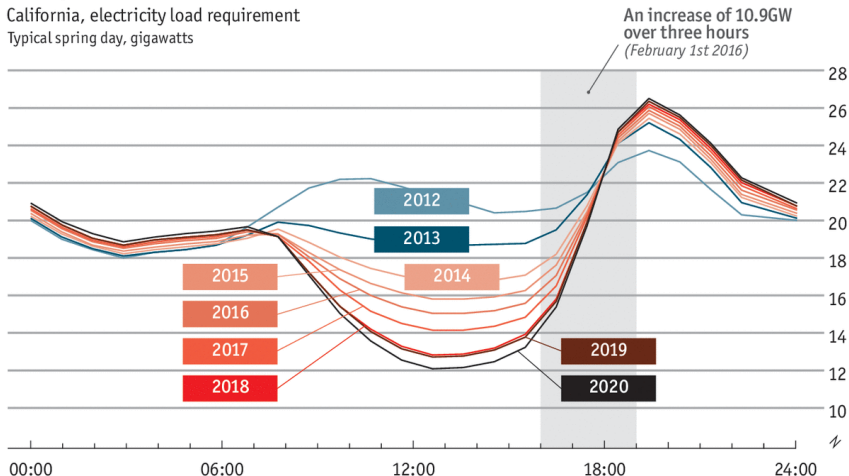
Here: 2007 vs. 2017 average daily EPEX prices for Germany/Austria



... in particular due to the 'duck curve' effect

Who gets the bill?

California, electricity load requirement
Typical spring day, gigawatts

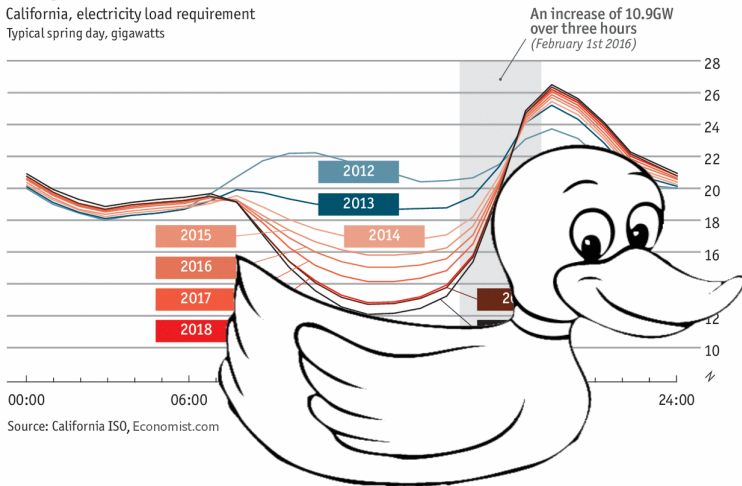


Source: California ISO, Economist.com

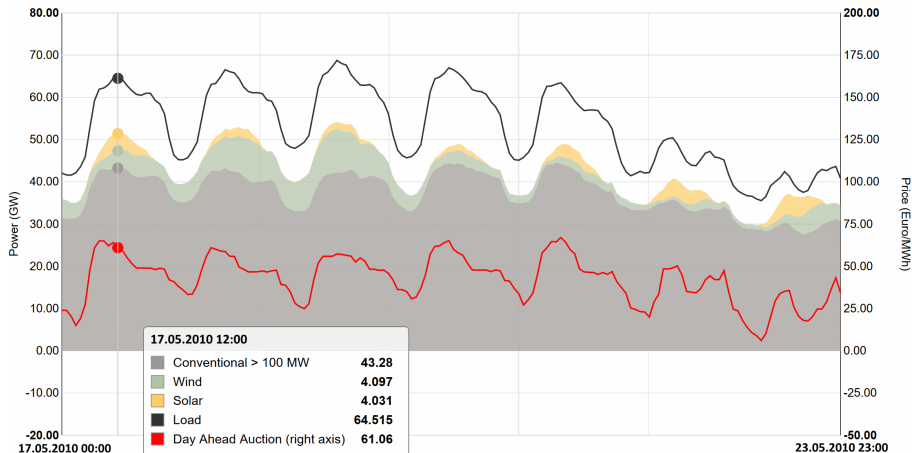
Where's the duck?

Who gets the bill?

California, electricity load requirement
Typical spring day, gigawatts

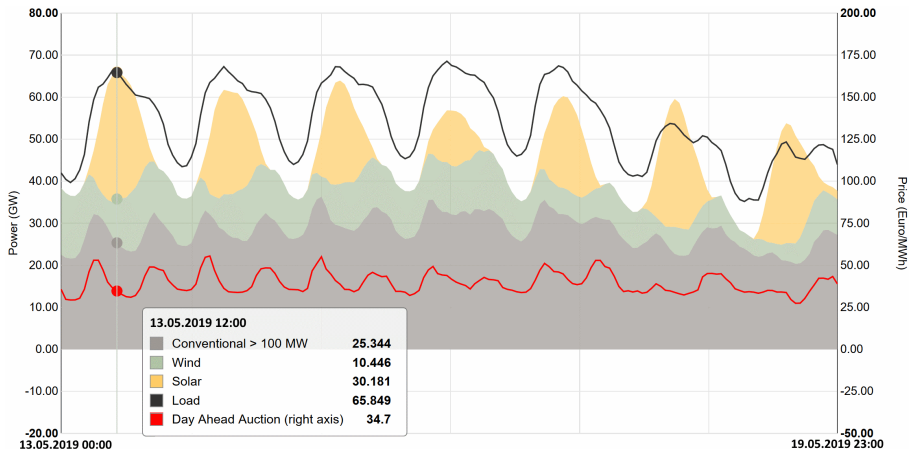


Germany 2010: No ducks



Source: www.energy-charts.de

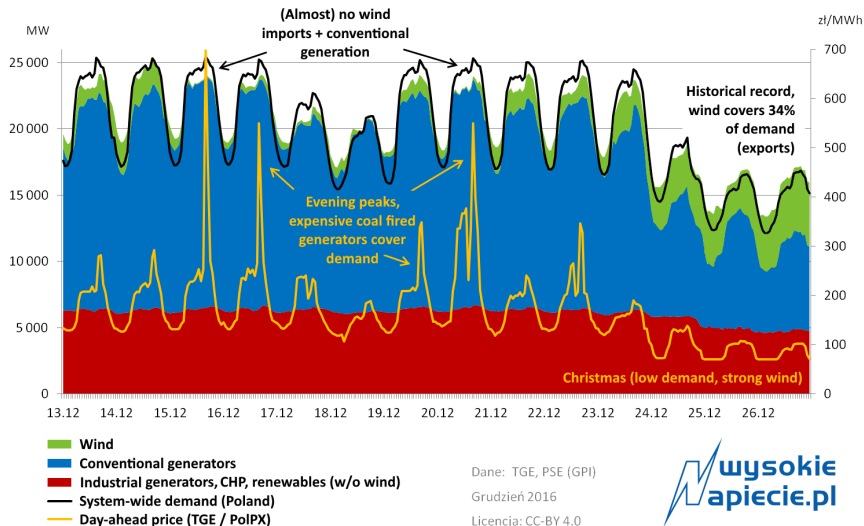
Germany 2019: 'Duck curve' (or 'peak shaving')



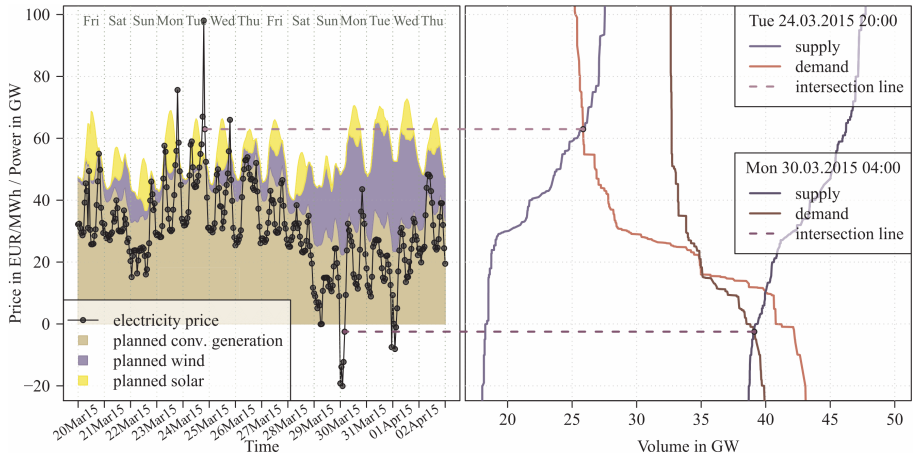
Source: www.energy-charts.de

What about wind infeed?

A closeup on two weeks in December 2016 in Poland



Supply and demand, renewables and negative prices



Source: Ziel & Steinert (2018, RSER)

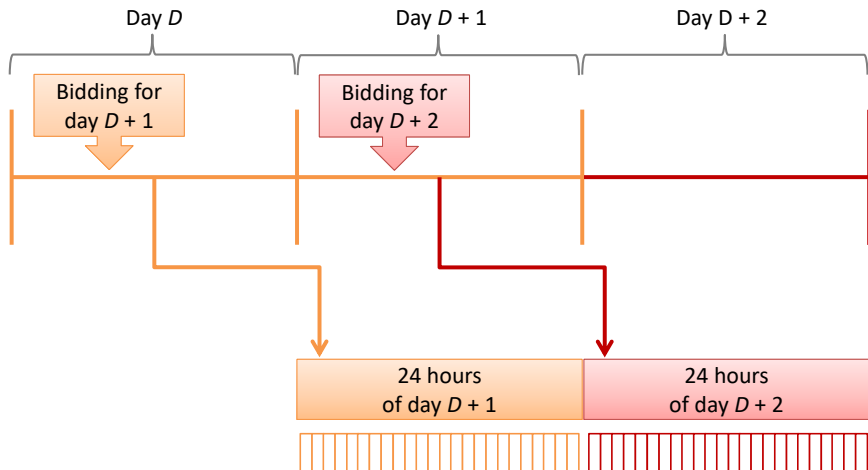
But why forecast electricity spot prices?

- 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**



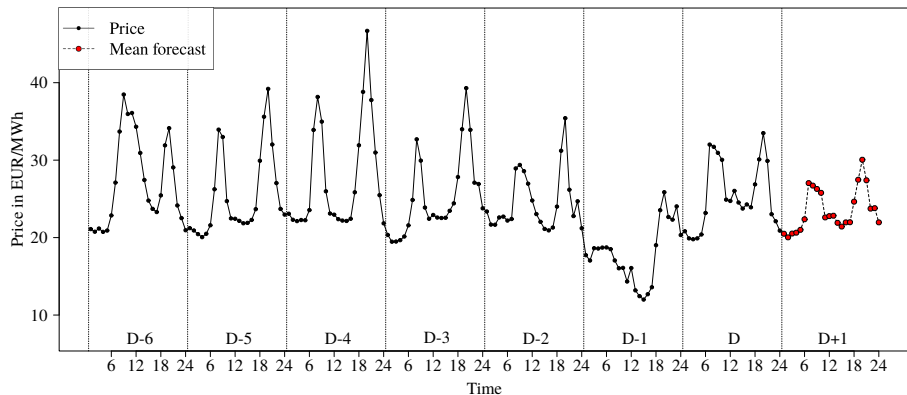
The workhorse of European power trading

The day-ahead market (ca. 93% of papers)

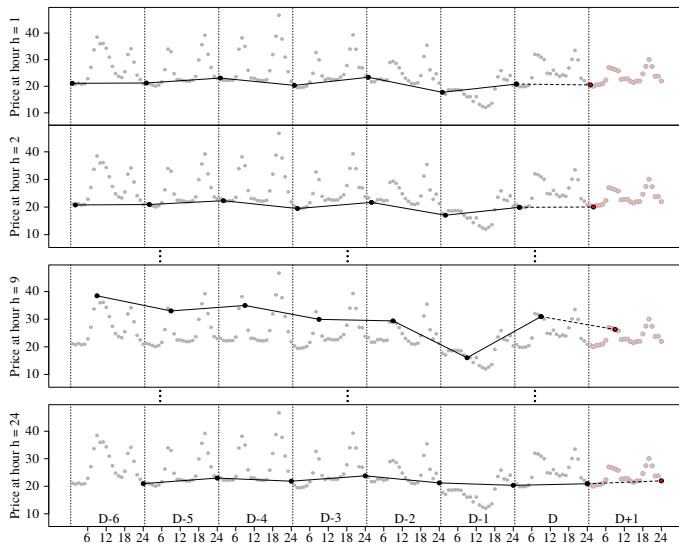


Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)



... or multivariate?

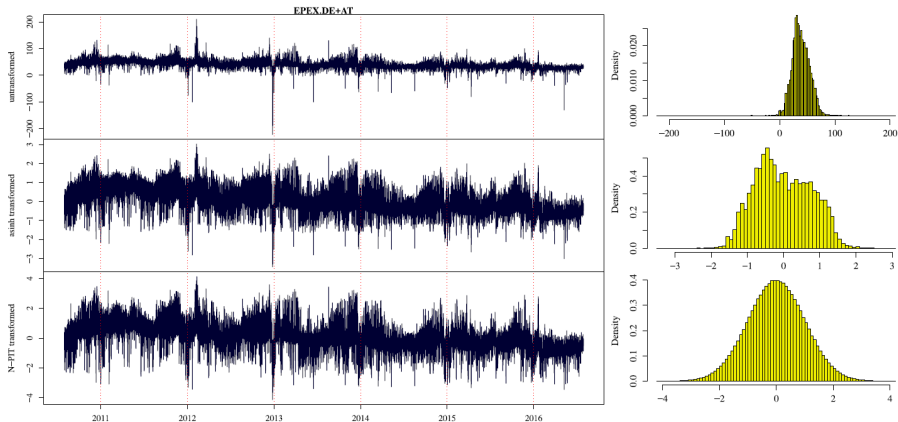


Dealing with asymmetry and heavy tails

(Uniejewski, Weron & Ziel, 2018, IEEE-TPWRS)

Variance stabilizing transformations (VSTs), e.g.,

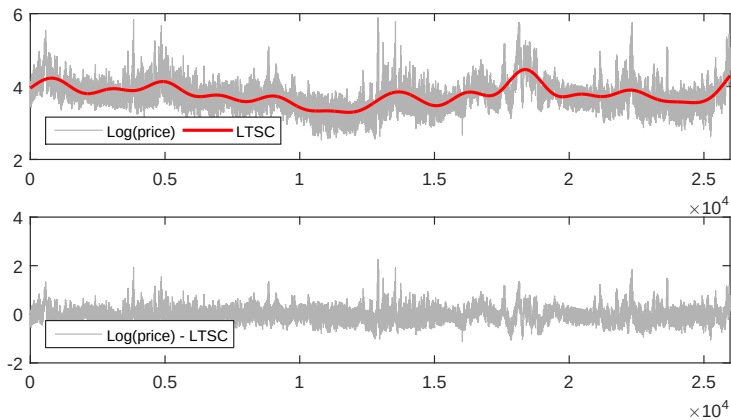
$$Y_{d,h} = \mathbf{asinh}(P_{d,h}) \equiv \log(P_{d,h} + \sqrt{P_{d,h}^2 + 1}) \text{ or } \mathbf{(N-)PIT}$$



What about seasonal decomposition?

(Nowotarski & Weron, 2016, ENEECO; Marcjasz et al., 2019, IJF)

Can the long-term trend-seasonal component (LTSC) impact short-term (day-ahead) electricity price forecasts?

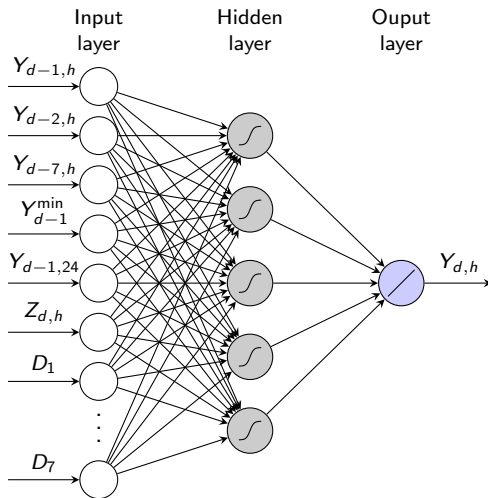


Day-ahead point forecasting: Regression ...

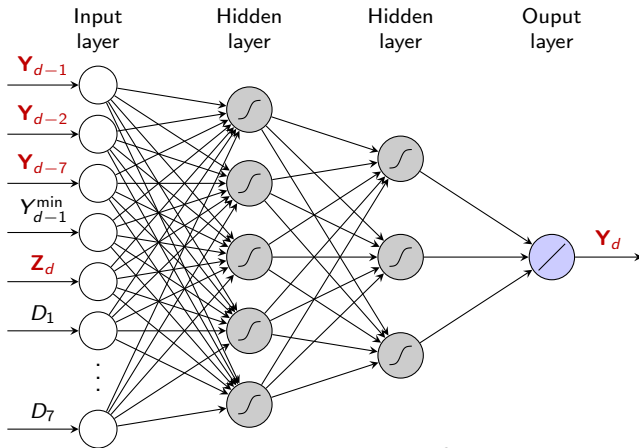
Electricity price for day d and hour h :

$$\begin{aligned}
 Y_{d,h} = & \underbrace{\beta_{h,1} Y_{d-1,h} + \beta_{h,2} Y_{d-2,h} + \beta_{h,3} Y_{d-7,h}}_{\text{autoregressive terms}} \\
 & + \underbrace{\beta_{h,4} Y_{d-1}^{\min}}_{\text{non-linear effect}} + \underbrace{\beta_{h,5} Y_{d-1,24}}_{\text{end-of-day effect}} + \underbrace{\beta_{h,6} Z_{d,h}}_{\text{load forecast}} \\
 & + \underbrace{\sum_{j=1}^7 \beta_{h,j+6} D_j}_{\text{weekday dummies}} + \varepsilon_{d,h},
 \end{aligned}$$

... neural nets ...

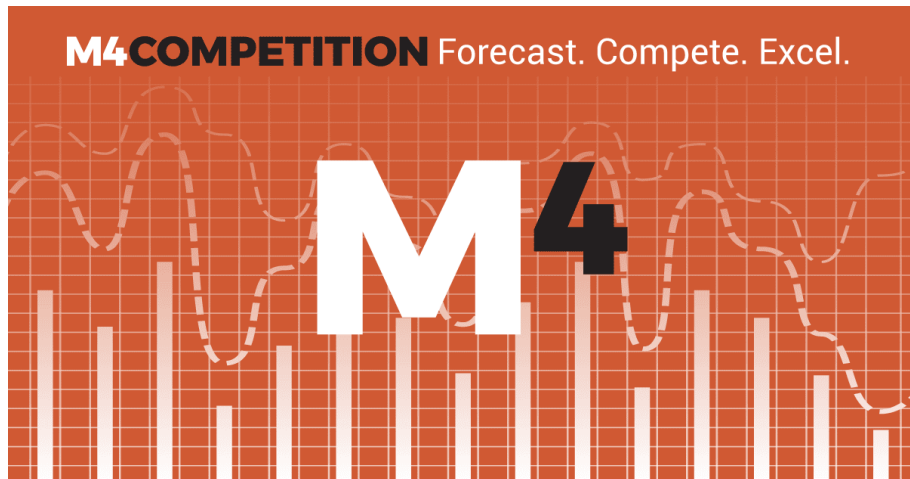


... or deep neural nets (DNN)?



NOTE: $\mathbf{Y}_d$ and $\mathbf{Z}_d$ are 24×1 vectors

What do the experts have to say?



Why bother with ML?



Spyros Makridakis @spyrosmakrid · 8 Jun 2018



2a/ The Combination of approaches was the king of the M4. Out of the 17 most accurate methods, 12 were Combinations of mostly statistical ones.



Spyros Makridakis @spyrosmakrid · 8 Jun 2018



5/ The five Machine Learning (ML) methods submitted in the M4 performed poorly, none of them being more accurate than the statistical benchmark and only one being more accurate than Naïve 2, finding consistent with our PLOS paper



Spyros Makridakis @spyrosmakrid · 8 Jun 2018



6/ The above findings suggest that individual statistical or ML methods are of limited value and that hybrid approaches and a combination of methods exploiting advantages and minimizing shortcomings is the way forward to improve f/casting accuracy and make f/casting more valuable

- Makridakis et al. (2018, PLoS ONE; 2018, IJF)

Really?



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(2019)

International Journal of Forecasting

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

On the importance of the long-term seasonal component in day-ahead electricity price forecasting with NARX neural networks

Grzegorz Marcjasz^{a,b}, Bartosz^a Department of Operations Research, Wrocław Univ^b Faculty of Pure and Applied Mathematics, Wrocław

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ARTICLE INFO

Keywords:

Electricity spot price

Forecasting

Day-ahead market

Long-term seasonal component

NARX neural network

Committee machine

Probabilistic electricity price forecasting with NARX networks: Combine point or probabilistic forecasts?

Grzegorz Marcjasz^{a,b}, Bartosz Uniejewski^{a,b}, Rafał Weron^{a,*}^a Department of Operations Research, Faculty of Computer Science and Management, Wrocław University of Science and Technology, Wrocław, Poland^b Faculty of Pure and Applied Mathematics, Wrocław University of Science and Technology, Wrocław, Poland

ARTICLE INFO

Keywords:

Electricity spot price

Probabilistic forecast

ABSTRACT

Recent electricity price forecasting studies have shown that decomposing a series of spot prices into a long-term trend-seasonal and a stochastic component, modeling them inde-

First read on electricity price forecasting (EPF)

R.Hyndman (EIC): "this paper alone is responsible for 0.7 of the $IF_{2016}=2.642$ " ;-)

International Journal of Forecasting 30 (2014) 1030–1081



Contents lists available at ScienceDirect

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

Institute of Organization and Management, Wrocław University of Technology, Wrocław, Poland



ARTICLE INFO

Keywords:

Electricity price forecasting
Day-ahead market
Seasonality
Autoregression
Neural network
Factor model
Forecast combination
Probabilistic forecast

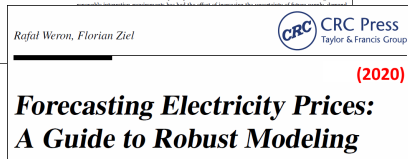
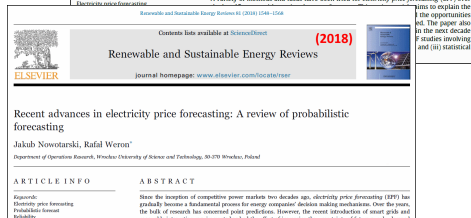
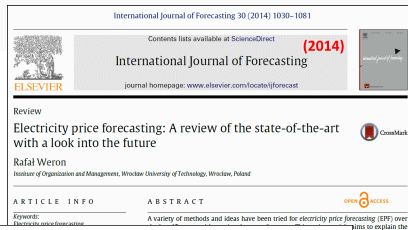
ABSTRACT

A variety of methods and ideas have been tried for electricity price the last 15 years, with varying degrees of success. This review article complexity of available solutions, their strengths and weaknesses, and threats that the forecasting tools offer or that may be encountered looks ahead and speculates on the directions EPF will or should take or so. In particular, it postulates the need for objective comparative testing of the significance of one model's outperformance of another



Agenda

- 1 Intro (a bit lengthy)
- 2 Variable selection
 - LASSO
- 3 Beyond point forecasts
 - Probabilistic, path
- 4 Combining forecasts
 - Point forecasts
 - Probabilistic forecasts
- 5 Combining revisited
 - Averaging across calibration windows
- 6 Intraday markets



Price autocorrelation: Today vs. yesterday

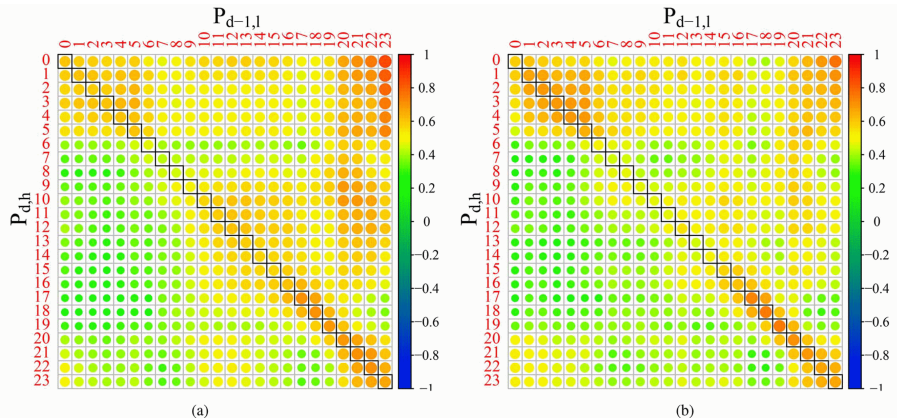


Fig. 1. Sample correlations of $\text{Cor}(P_{d,h}, P_{d-1,l})$ for $h, l = 0, \dots, 23$ and two markets from 17.12.2009 to 12.08.2014. (a) EPEX spot price for Germany and Austria, (b) APX spot price for Netherlands.

Source: Ziel (2016, IEEE-TPWRS)

Variable (feature, input) selection using LASSO

(Uniejewski et al., 2016, Energies; Ziel, 2016, IEEE-TPWRS; Ziel & Weron, 2018, ENEECO)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24		
$\beta_{0,10}$	21.42	10.01	9.08	21.81	21.98	11.41	12.62	11.04	12.07	8.96	8.90	8.62	7.05	8.45	5.13	5.93	5.17	6.92	1.63	5.26	4.87	9.18	13.51	19.85			
$\beta_{1,10}$	41.75	24.36	18.87	4.88	5.44	11.05	16.98	9.40	7.99	6.77	10.67	7.19	6.35	10.18	11.18	10.78	8.47	4.45	4.91	5.98	6.20	5.92	10.19	20.72			
$\beta_{2,10}$	41.75	24.36	18.87	4.88	5.44	11.05	16.98	9.40	7.99	6.77	10.67	7.19	6.35	10.18	11.18	10.78	8.47	4.45	4.91	5.98	6.20	5.92	10.19	20.72			
$\beta_{3,10}$	21.80	21.99	20.28	20.34	10.34	10.06	3.29	3.25	4.58	4.36	3.61	2.66	1.26	3.67	6.02	6.25	6.42	1.02	3.02	3.37	2.65	3.64	1.14	9.88			
$\beta_{4,10}$	22.55	28.35	28.35	51.17	63.97	45.06	13.08	15.64	16.55	25.18	15.80	10.60	11.89	7.81	5.01	5.98	4.77	1.14	0.54	5.41	7.99	5.30	6.60				
$\beta_{5,10}$	19.64	41.85	34.22	54.20	70.06	42.67	20.43	12.95	12.71	6.73	8.12	7.24	4.28	4.07	3.16	2.58	2.59	2.29	4.01	4.41	1.91	4.47					
$\beta_{6,10}$	18.87	17.46	18.22	18.22	19.88	9.02	2.62	2.44	10.71	8.90	3.48	7.14	11.14	10.44	10.70	7.74	6.96	5.98	4.34	3.47	6.77	0.27					
$\beta_{7,10}$	10.51	10.08	15.96	16.44	10.73	79.99	5.14	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	
$\beta_{8,10}$	4.58	1.22	3.04	3.29	3.29	4.73	3.44	10.40	20.01	16.02	6.00	5.66	11.84	13.56	11.07	12.27	20.25	12.17	7.87	6.27	3.52	3.69	2.94				
$\beta_{9,10}$	1.08	0.67	1.70	1.34	2.71	4.41	2.55	18.85	6.55	2.52	10.24	4.29	3.46	7.52	10.73	17.44	20.05	29.79	14.38	10.66	5.65	7.72	4.44	3.94			
$\beta_{10,10}$	0.32	0.19	0.40	0.56	0.56	0.48	0.58	2.58	11.75	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	
$\beta_{11,10}$	0.38	0.54	3.93	5.93	12.65	8.56	6.02	2.27	5.97	27.63	33.1	23.71	7.70	1.39	0.61	2.69	6.35	4.80	6.10	4.80	2.32	2.24	0.15				
$\beta_{12,10}$	2.80	2.15	2.08	10.61	10.66	5.85	5.27	5.58	4.75	6.53	13.51	25.46	26.51	10.98	3.80	1.42	8.82	3.80	5.62	1.76	1.72	2.31	4.54	2.72			
$\beta_{13,10}$	8.11	3.18	5.33	6.03	7.05	3.59	6.25	6.73	6.23	16.78	12.38	45.57	55.45	21.21	8.21	4.38	1.85	2.65	1.80	0.90	0.90	2.54	1.36	1.00			
$\beta_{14,10}$	5.89	5.40	5.01	1.54	1.20	1.08	1.08	5.44	6.44	22.38	30.49	28.80	36.55	43.31	21.81	8.59	3.2	0.80	0.74	0.61	2.31	1.68	2.48				
$\beta_{15,10}$	8.71	8.36	5.89	0.84	4.72	4.99	11.28	21.49	22.10	25.10	30.27	41.13	37.42	40.41	10.64	6.17	4.26	4.36	3.91	1.24	0.88	8.81					
$\beta_{16,10}$	15.47	17.07	7.86	5.12	5.31	10.53	10.53	4.96	7.90	8.58	14.35	28.22	35.94	46.70	10.40	6.02	7.11	23.70	8.54	3.82	1.66	1.66	2.20	2.32			
$\beta_{17,10}$	18.87	17.46	18.87	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	38.24	
$\beta_{18,10}$	10.51	10.08	15.96	16.44	10.73	79.99	5.14	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	1.73	
$\beta_{19,10}$	20.83	30.61	34.53	23.02	23.11	49.99	63.97	61.77	42.97	41.38	30.46	22.37	22.37	19.98	18.18	17.98	43.84	94.50	46.20	7.63	3.84	9.03					
$\beta_{20,10}$	15.96	15.97	23.84	23.84	23.84	45.30	77.22	60.11	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	67.79	
$\beta_{21,10}$	38.14	38.14	38.14	45.70	47.89	46.80	70.33	61.18	68.10	68.56	63.11	64.87	52.10	48.29	47.12	47.99	42.08	23.12	24.52	28.85	51.94	92.58	41.11	10.34	16.59		
$\beta_{22,10}$	30.38	22.52	18.56	18.73	22.85	17.96	25.37	30.99	41.82	50.92	62.93	70.34	65.87	63.04	57.70	56.03	51.40	46.40	38.14	37.16	32.31	63.09	98.04	67.07			
$\beta_{23,10}$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
$\beta_{24,10}$	11.33	11.67	7.23	5.03	4.41	8.60	12.34	6.97	4.28	5.55	4.67	8.33	8.32	8.02	7.12	5.81	4.00	6.00	5.11	3.81	3.22	3.82	2.80	10.75			
$\beta_{25,10}$	8.36	10.18	10.61	8.20	5.98	12.08	4.63	12.38	11.78	8.46	5.96	5.47	6.82	7.90	7.75	6.90	9.76	8.52	7.84	4.85	6.64	3.61	1.80	5.23			
$\beta_{26,10}$	7.46	7.07	17.57	28.57	20.01	20.24	15.02	14.12	10.38	4.21	4.35	2.68	2.05	2.60	2.60	2.60	2.60	2.60	2.60	2.60	2.60	2.60	2.60	2.60	2.60	2.60	
$\beta_{27,10}$	28.03	22.72	16.28	11.32	44.40	26.97	23.42	26.64	17.51	11.66	7.71	3.55	6.29	5.84	8.70	8.59	6.37	5.43	6.28	1.62	0.28	2.31	4.51	6.02			
$\beta_{28,10}$	5.86	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	6.58	12.60	
$\beta_{29,10}$	7.76	7.04	6.93	8.51	7.69	5.85	13.83	10.65	5.23	1.87	2.63	2.38	6.14	7.68	5.06	3.22	3.08	6.70	8.50	2.54	0.80	0.49	1.06	1.11			
$\beta_{30,10}$	6.98	4.69	8.94	4.69	10.46	14.53	7.63	8.62	3.82	3.07	5.20	6.65	11.17	10.30	12.12	12.32	10.38	4.87	4.20	2.05	1.54	5.71	3.70				
$\beta_{31,10}$	4.38	4.91	8.94	4.91	7.16	8.94	4.91	8.94	4.91	7.16	8.94	4.91	7.16	8.94	4.91	7.16	8.94	4.91	7.16	8.94	4.91	7.16	8.94	4.91	7.16	8.94	
$\beta_{32,10}$	6.98	3.38	9.78	12.23	8.61	8.68	2.44	6.97	8.20	1.41	0.90	0.71	1.31	1.39	3.80	5.87	8.54	3.85	4.53	2.51	1.85	1.33	0.29				
$\beta_{33,10}$	4.12	5.48	8.98	5.48	8.98	7.08	8.98	5.48	8.98	7.08	8.98	5.48	8.98	7.08	8.98	5.48	8.98	7.08	8.98	5.48	8.98	7.08	8.98	5.48	8.98	7.08	8.98
$\beta_{34,10}$	2.87	7.09	10.28	16.54	15.03	8.20	2.49	3.59	3.92	2.10	4.87	2.02	10.04	4.87	2.02	10.04	4.87	2.02	10.04	4.87	2.02	10.04	4.87	2.02	10.04	4.87	2.02
$\beta_{35,10}$	1.80	2.15	7.18	9.78	9.10	9.10	9.30	4.27	2.52	1.90	0.57	0.57	20.39	10.52	8.47	5.60	2.51	4.66	10.73	1.73	2.42	0.82	4.77	2.99			
$\beta_{36,10}$	0.64	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	8.47	3.70	
$\beta_{37,10}$	0.63	2.80	7.82	8.78	11.00	8.52	11.71	12.04	5.29	1.82	2.79	8.16	8.21	7.86	5.62	6.28	6.18	2.34	6.29	1.78	2.78	0.22	2.89				
$\beta_{38,10}$	2.25	3.84	5.80	6.00	7.62	5.76	1.89	4.40	2.91	2.73	1.85	4.04	4.37	5.83	3.29	8.08	11.22	12.28	6.61	1.26	1.26	1.26	1.26	1.26	1.26	1.26	
$\beta_{39,10}$	1.87	2.48	7.08	6.49	9.29	9.29	4.29	7.67	4.81	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	1.21	
$\beta_{40,10}$	0.49	5.17	7.99	6.99	7.79	6.17	6.30	6.01	1.53	1.50	2.35	4.88	14.13	16.96	21.02	15.14	15.58	7.947	18.41	2.30	1.75	3.75	3.82	6.15			
$\beta_{41,10}$	1.15	0.78	4.89	1.15	0.78	4.89	1.15	0.78	4.89	1.15	0.78	4.89	1.15	0.78	4.89	1.15	0.78	4.89	1.15	0.78	4.89	1.15	0.78	4.89	1.15	0.78	
$\beta_{42,10}$	8.36	4.10	4.47	6.34	3.20	8.83	8.58	4.52	1.57	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77	1.77		
$\beta_{43,10}$	10.20	15.78	20.62	28.96	20.19	13.22	9.02	16.27	1.90	9.20	9.18	7.61	8.30	15.20	15.73	14.12	10.50	9.22	6.08	2.05	70.64	18.00	11.22	8.16			
$\beta_{44,10}$	17.33	11.16	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32	25.32		
$\beta_{45,10}$	20.57	25.48	36.76	34.48	41.17	42.37	16.57	18.53	14.87	11.26	13.40	15.51	9.50	7.35	7.87	12.02	4.67	2.57	6.25	6.05	13.18	40.40	30.34				
$\beta_{46,10}$	14.97	14.98	14.98	15.56	34.54	28.40	16.97	16.40	12.55	10.68	10.74	10.74	22.76	10.53	10.50	14.30	9.95	2.97	7.23	14.40	27.42						

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Review

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

Rafał Weron

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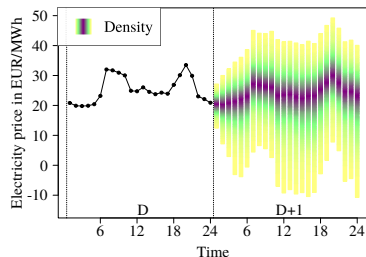
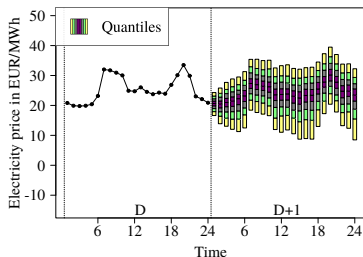
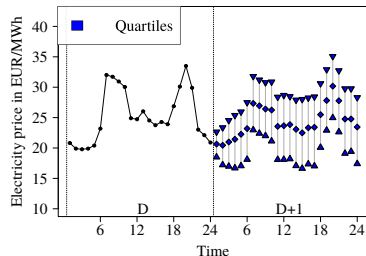
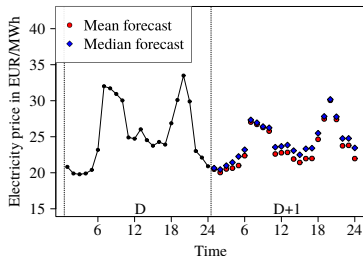
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CRC Press
Taylor & Francis Group

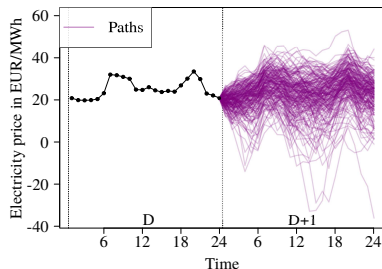
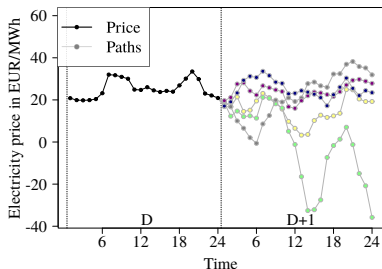
**Forecasting Electricity Prices:
A Guide to Robust Modeling**

A new hype: Point $\rightarrow$ probabilistic forecasting

(ca. 7% of EPF papers)



Not yet a hype: Probabilistic $\rightarrow$ path forecasting



- Relatively novel in EPF (but not in weather forecasting)
- Operational decisions often depend on prices for multiple hours in a row (e.g., ramping costs of power plants)
- Regulatory incentives: in Germany a wind park can receive less subsidies if the electricity price is negative for 6 hours in a row

(Very) recent reviews of probabilistic EPF



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(2018)

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Probabilistic mid- and long-term electricity price forecasting

Florian Ziel^{a,*}, Rick Steinert^b

^a Universität Duisburg-Essen, Berliner Platz 6-8, 45127 Essen, Germany

^b Europa-Universität Viadrina, Große Schärnstraße 59, 15230 Frankfurt, Oder, Germany



ARTICLE INFO

Keywords:

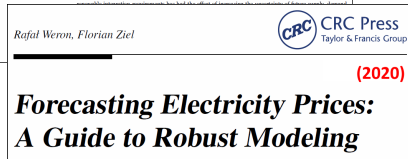
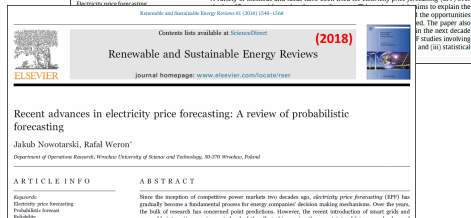
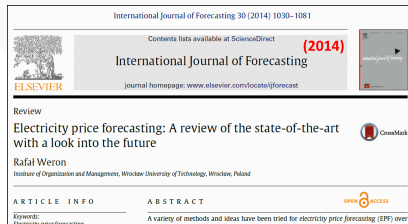
Electricity prices
Probabilistic forecasting

ABSTRACT

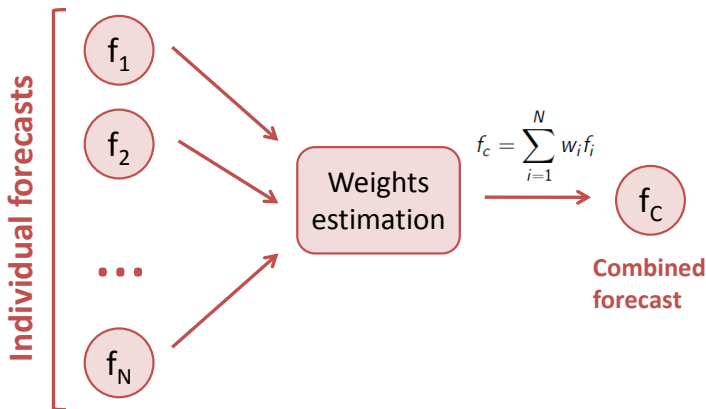
The liberalization of electricity markets and the development of renewable energy sources has led to new challenges for decision makers. These challenges are accompanied by an increasing uncertainty about future . . .

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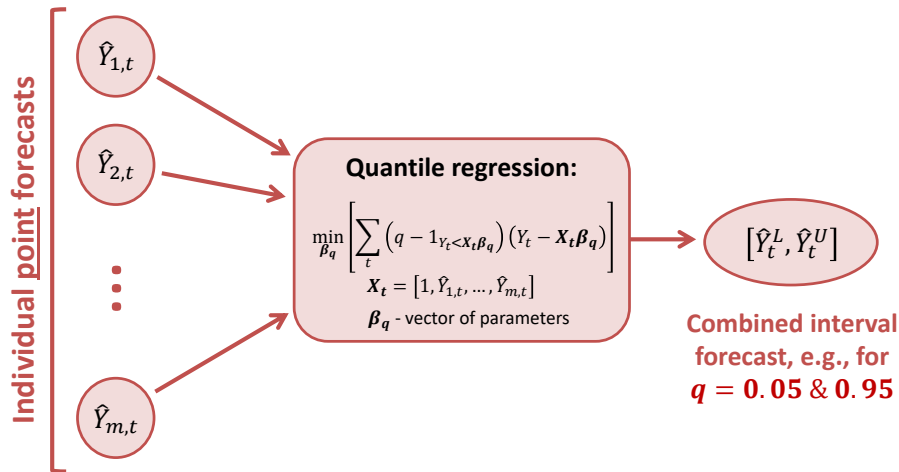
Point forecast averaging: The idea



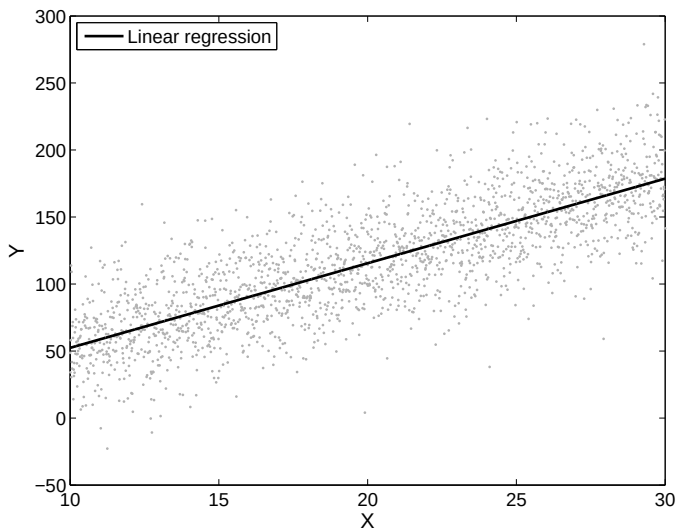
- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger

Quantile Regression Averaging: The idea

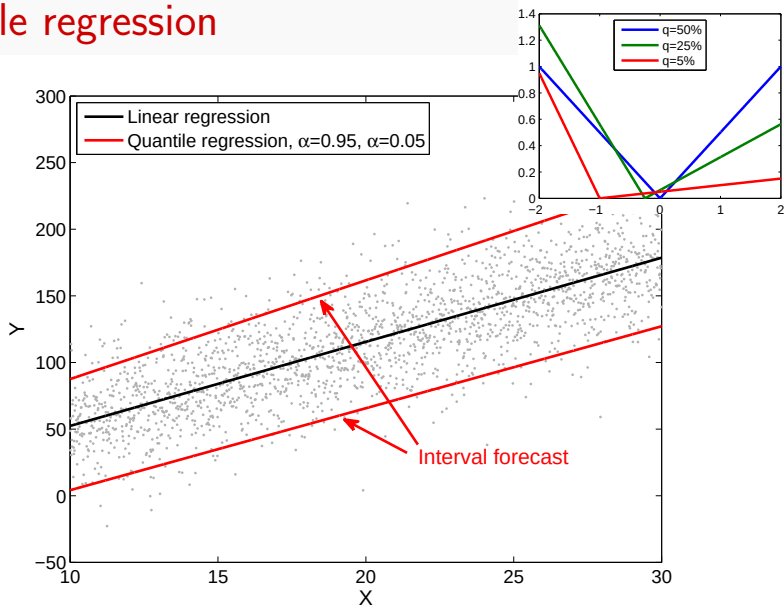
(Nowotarski & Weron, 2015, Comp. Statist.)



Quantile regression

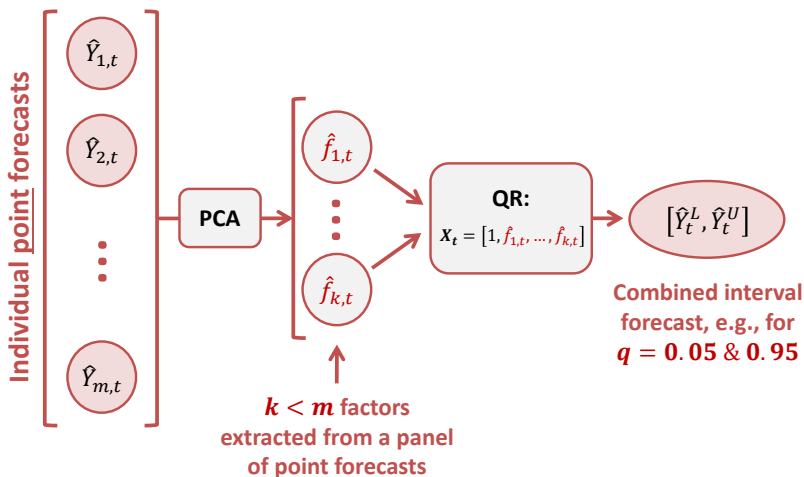


Quantile regression



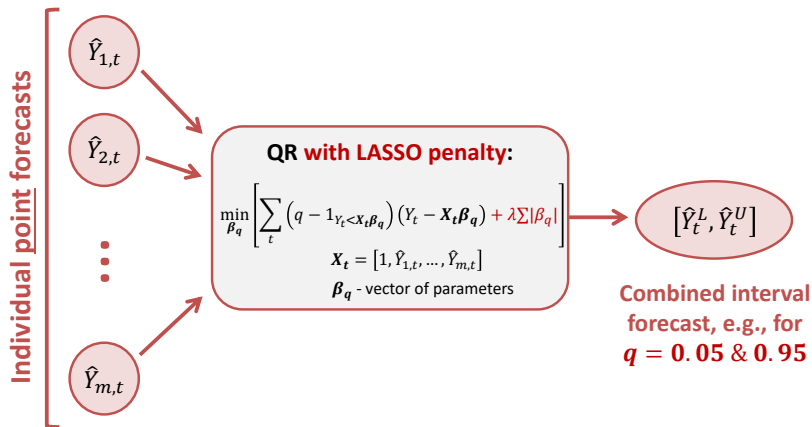
FQRA: When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



LASSO QRA (LQRA): An alternative to FQRA

(Uniejewski & Weron, 2019, WP)



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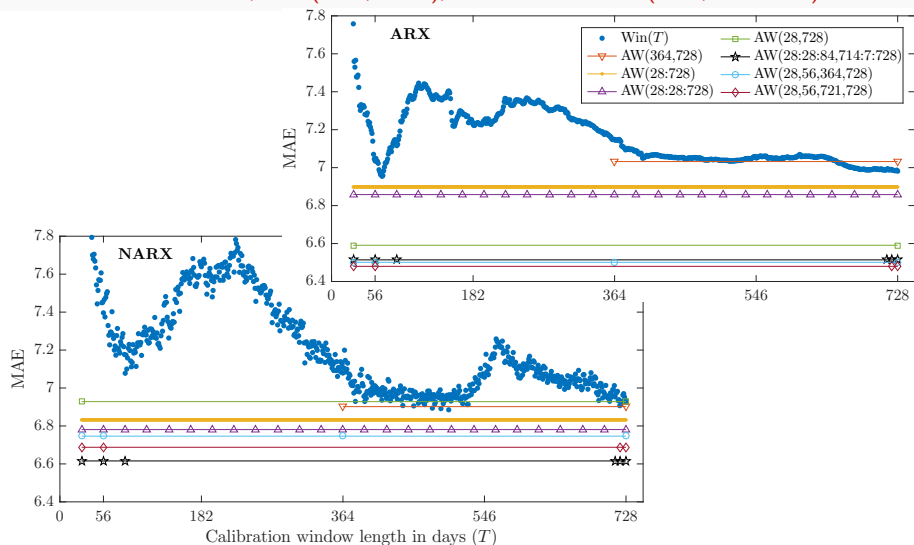
CRC Press
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(2020)

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Averaging across calibration windows

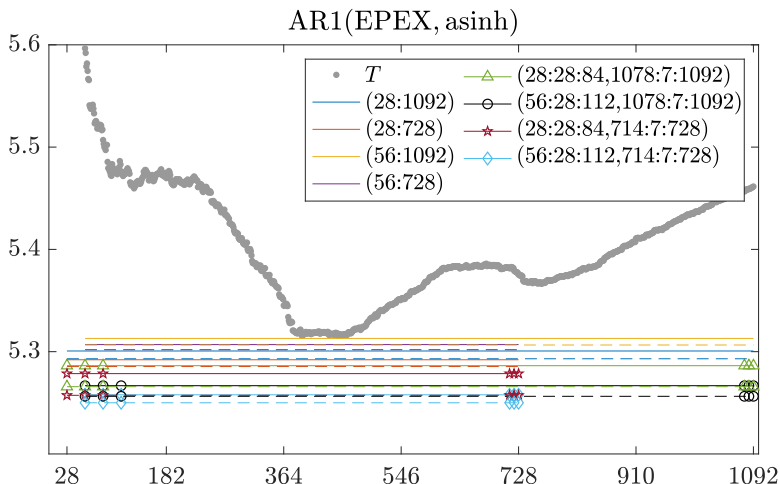
Structural breaks: Pesaran, Pick (2011, JBES); EPF: Hubicka et al. (2019, IEEE-TSE)



Past performance-weighted averaging

(Marcjasz, Serafin & Weron, 2018, Energies)

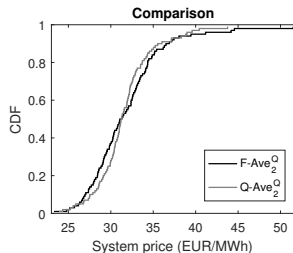
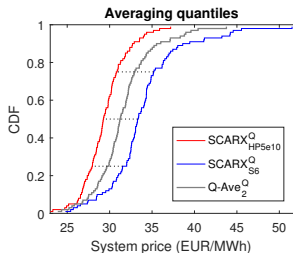
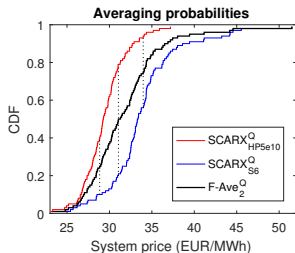
'—' AW, '- -' WAW



Combining probabilistic forecasts is more tricky

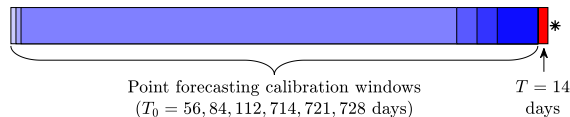
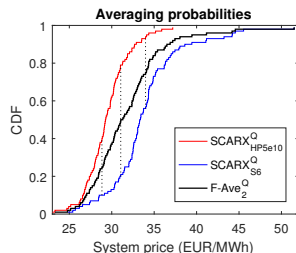
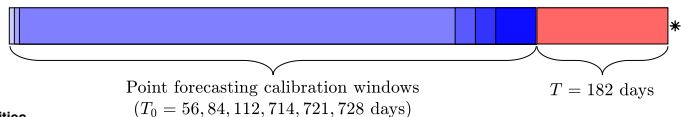
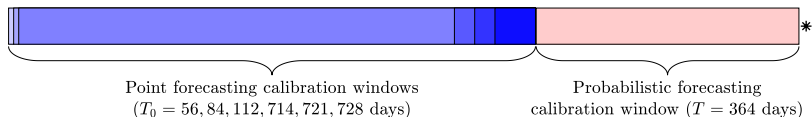
(Lichtendahl et al., 2013, Mngt Sci)

- Average probability forecast: $\mathbf{F-Ave}_n^* \equiv \frac{1}{n} \sum_{i=1}^n \hat{F}_i(x)$
- Average quantile forecast: $\mathbf{Q-Ave}_n^* \equiv \hat{Q}^{-1}(x)$
with $\hat{Q}(x) = \frac{1}{n} \sum_{i=1}^n \hat{Q}_i(x)$ and quantile forecast $\hat{Q}_i(x) = \hat{F}_i^{-1}(x)$

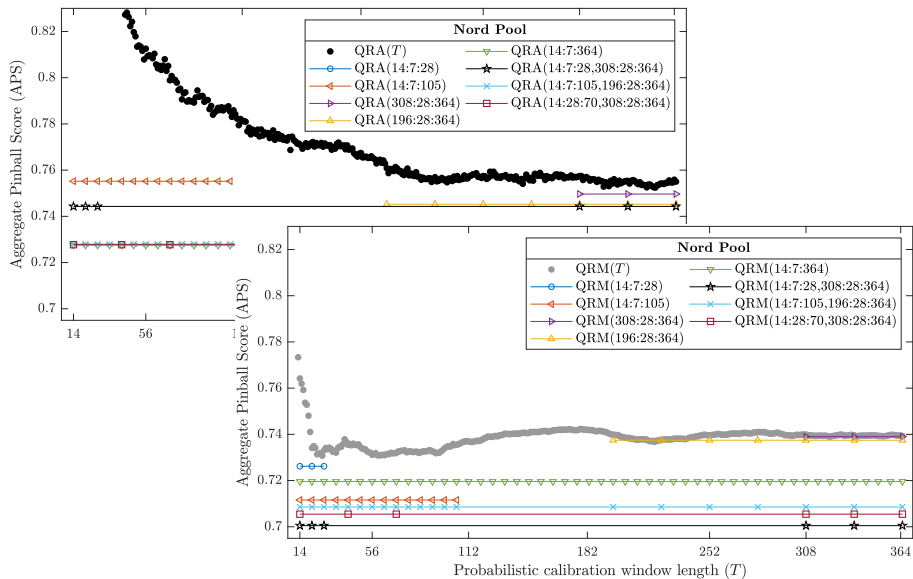


Also works for probabilistic forecasts

(Serafin, Uniejewski & Weron, 2019, Energies)

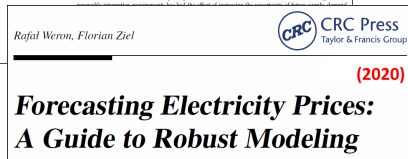
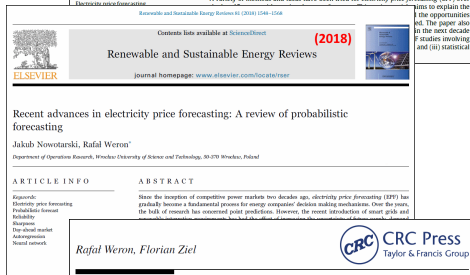


QRA vs. QRM (QR Machine)

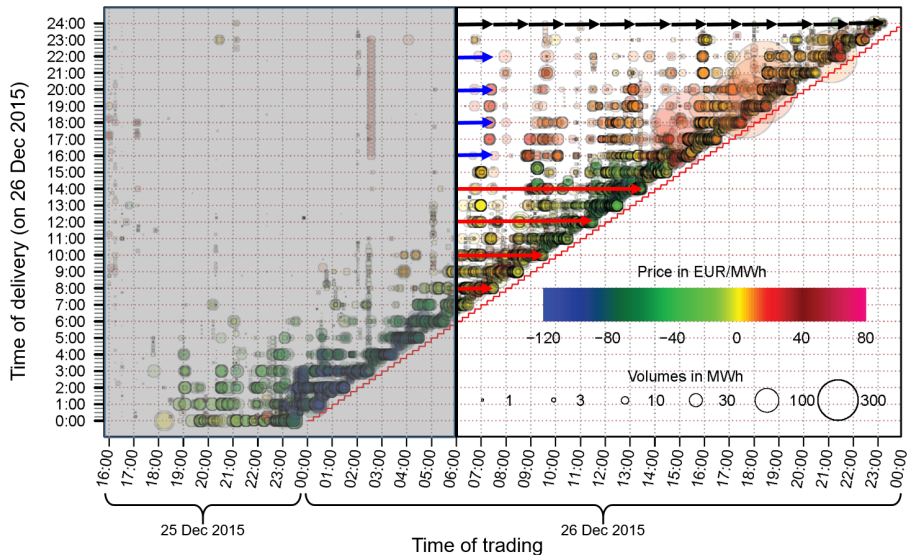


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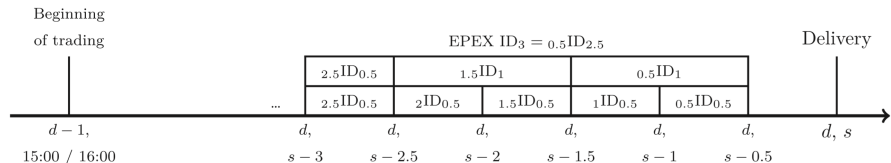
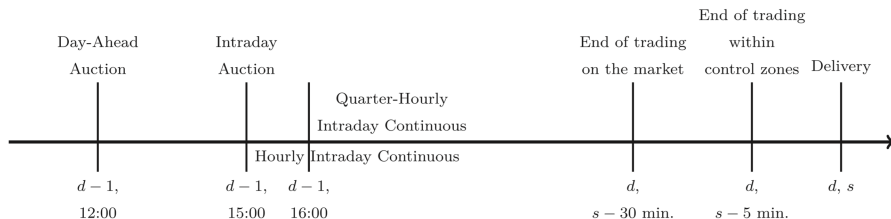


A continuous, not an auction market



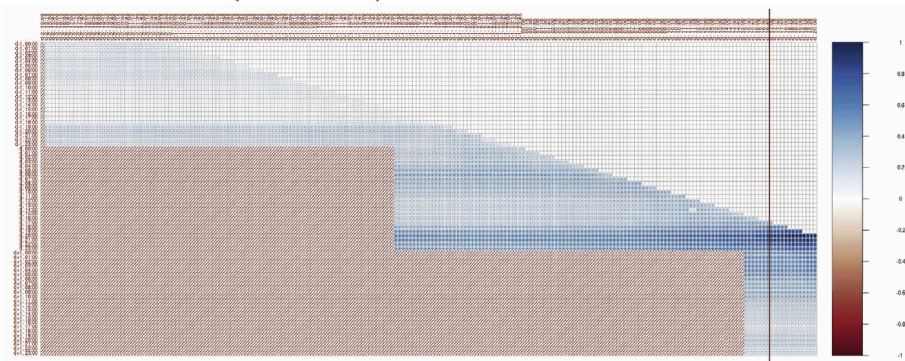
Timeline of events and the ID3 index

(Narajewski & Ziel, 2020, JCM)



A (weak form) efficient market?

Narajewski & Ziel (2020, JCM): Yes, the last price is the best predictor:



Marcjasz, Uniejewski & Weron (2020, WP): No, we can beat the naive ;-)

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