Recent advances in electricity price forecasting: A MMXX (i.e., 2020) perspective

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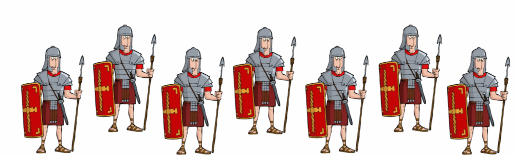
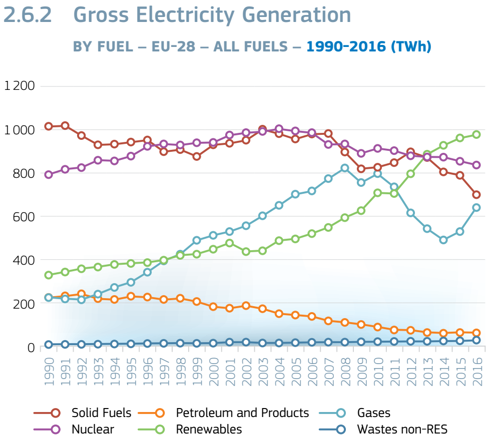
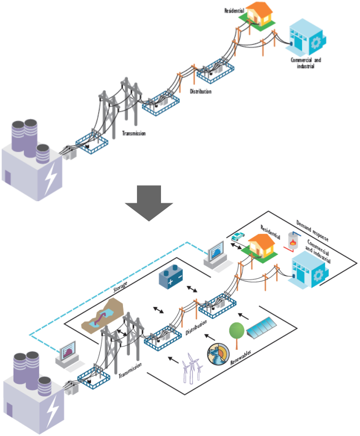


*Based on work with K.Hubicka, A.Kaszuba, K.Maciejowska, G.Marcjasz, W.Nitka, T.Serafin, B.Uniejewski (PWr)
J.Lago (Delft), J.Nowotarski (BNY Mellon), M.Zator (Kellogg), C.Kath, F.Ziel (Essen)

Power markets are undergoing a transformation ...

The resource mix transitions from fossil fuels to renewables

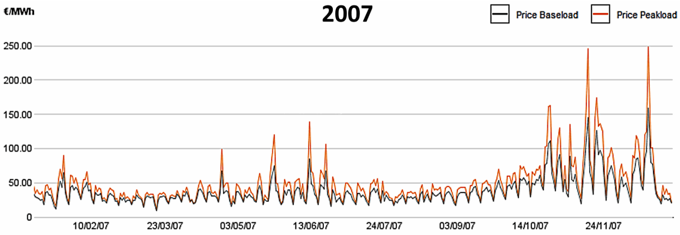


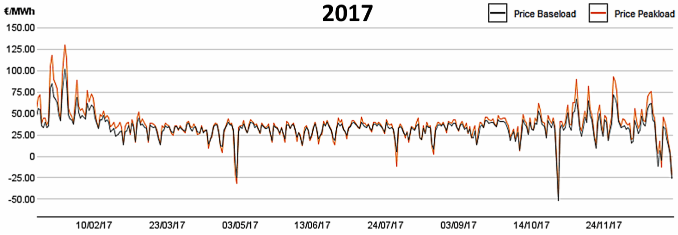


Sources: EU (2018), Adigbli (2017)

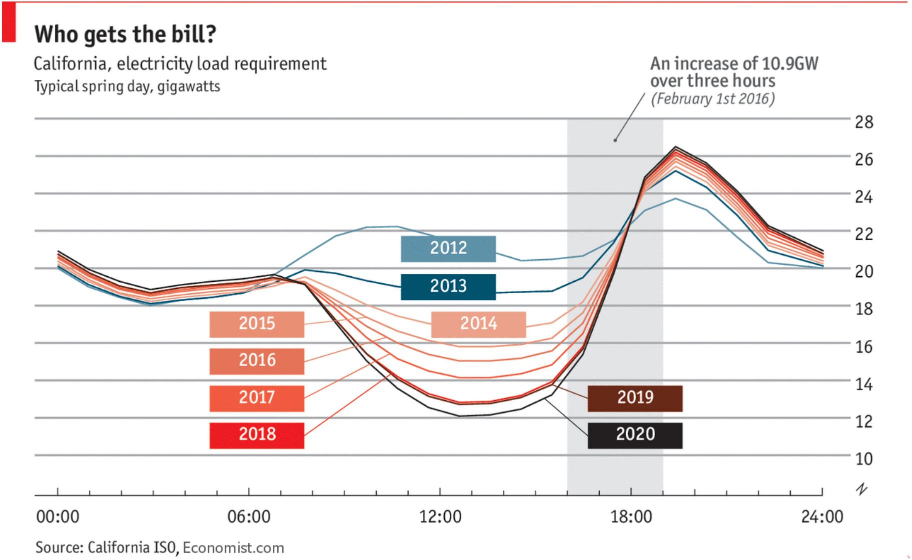
... and the price characteristics are changing ...

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

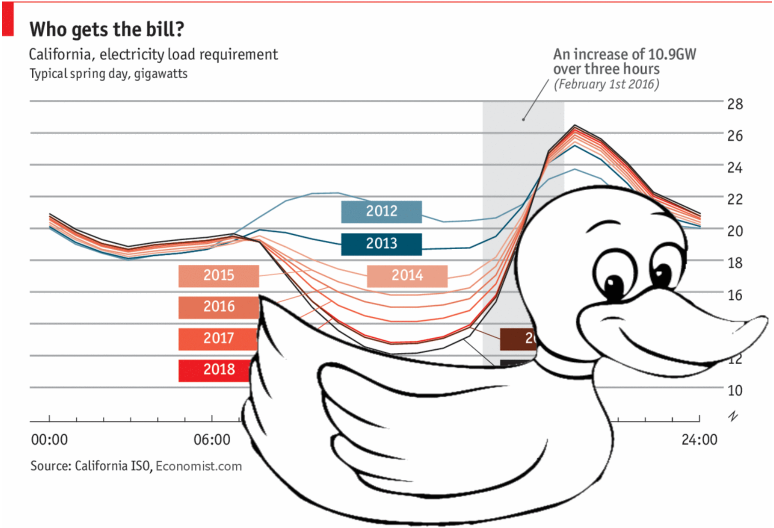




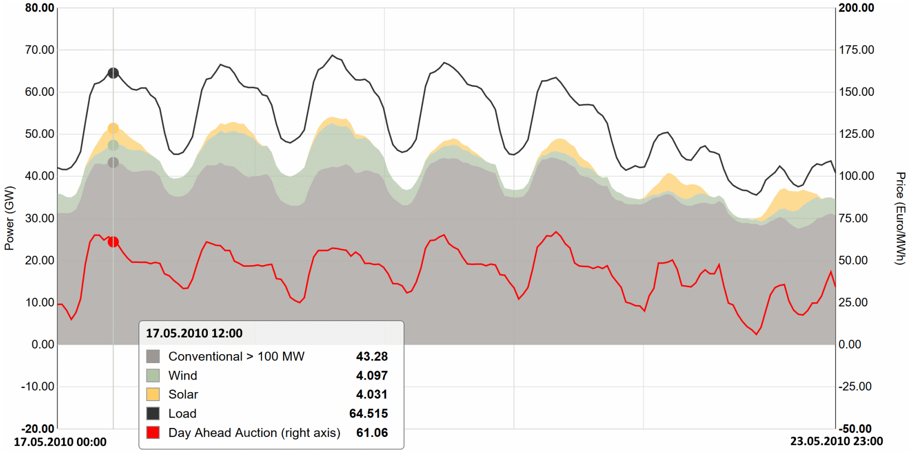
… in particular due to the 'duck curve' effect



Where's the duck?

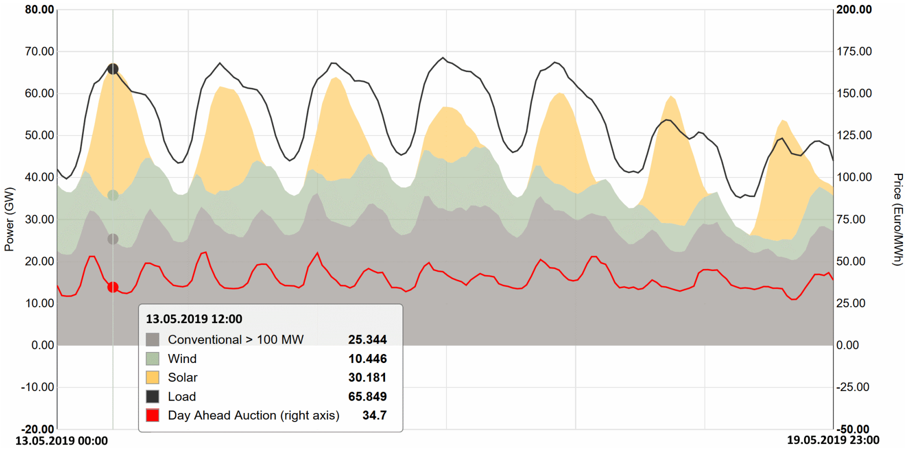


Germany 2010: No ducks



Source: www.energy-charts.de

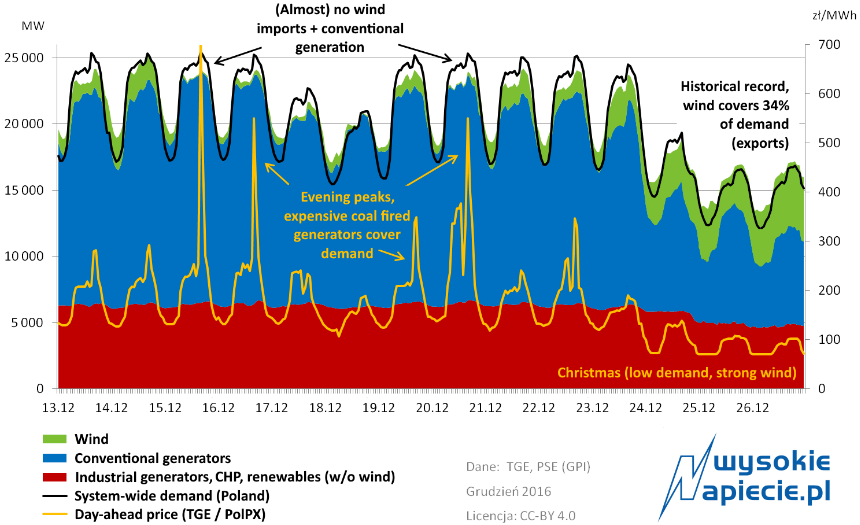
Germany 2019: ‘Duck curve’ (or ‘peak shaving’)



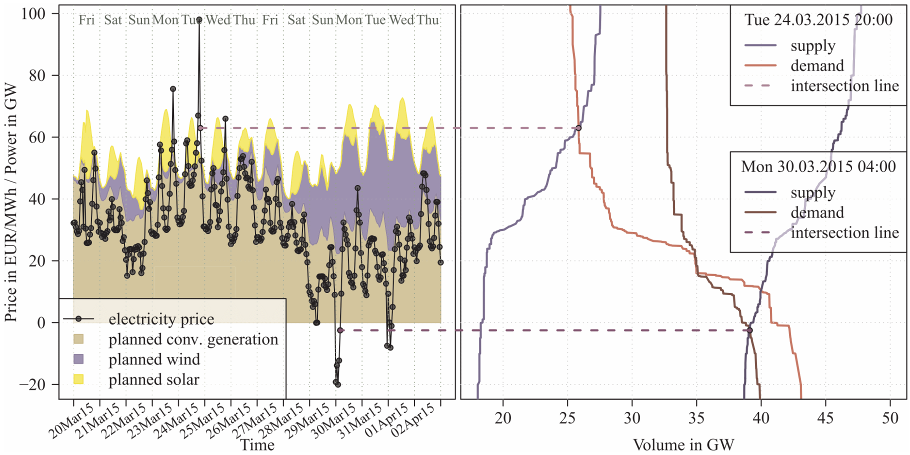
Source: www.energy-charts.de

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)

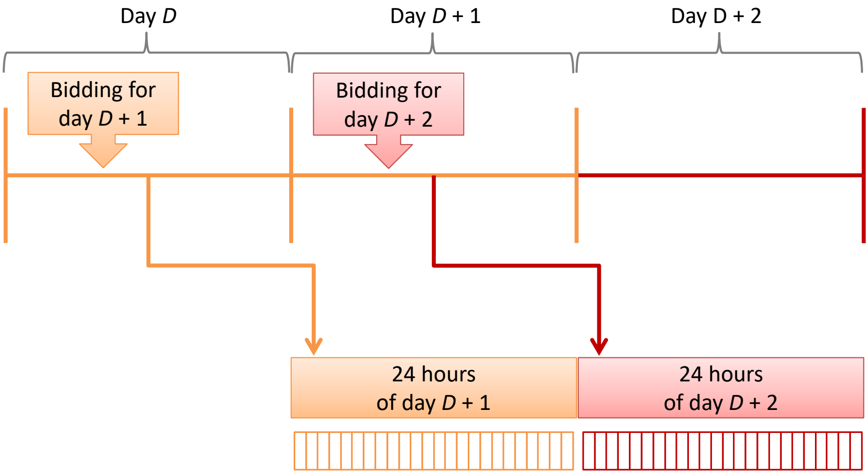
But why forecast electricity spot prices?

- 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

eex	EPEXSPOT		TSO
DERIVATIVES >	DAY-AHEAD >	INTRADAY >	BALANCING
Years/months/weeks before delivery	One day before delivery	<1 hour before delivery	Real-time
Price variations are HEDGED	**Optimization of GENERATION**	**Valuation of FLEXIBILITY**	**Ensuring SYSTEM SECURITY**

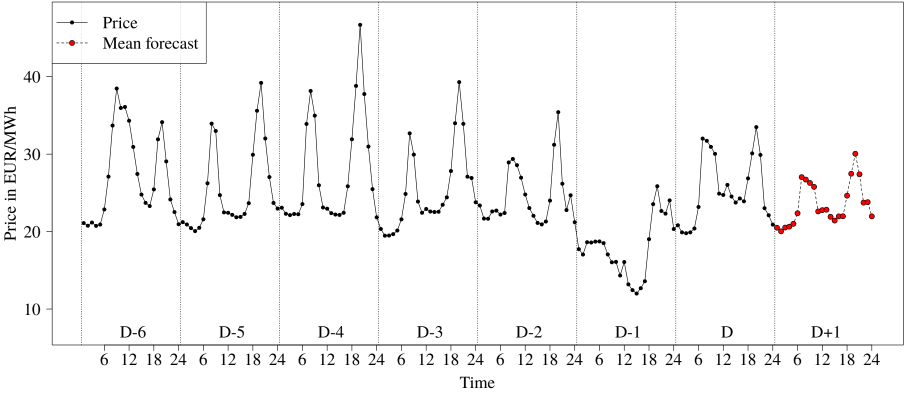
The workhorse of European power trading

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

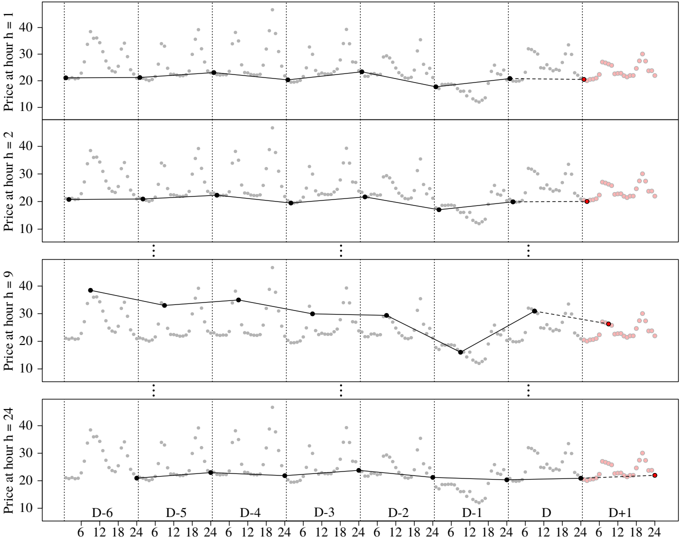


Day-ahead point forecasting: Univariate ...

(Ziel & Weron, 2018, ENEECO)

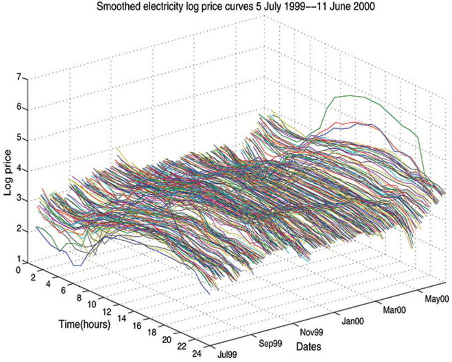


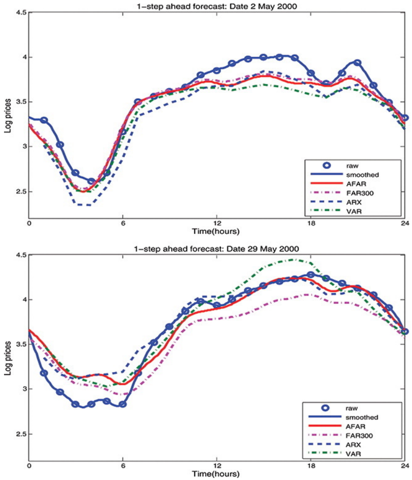
... multivariate ...



... or functional (data analysis)?

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



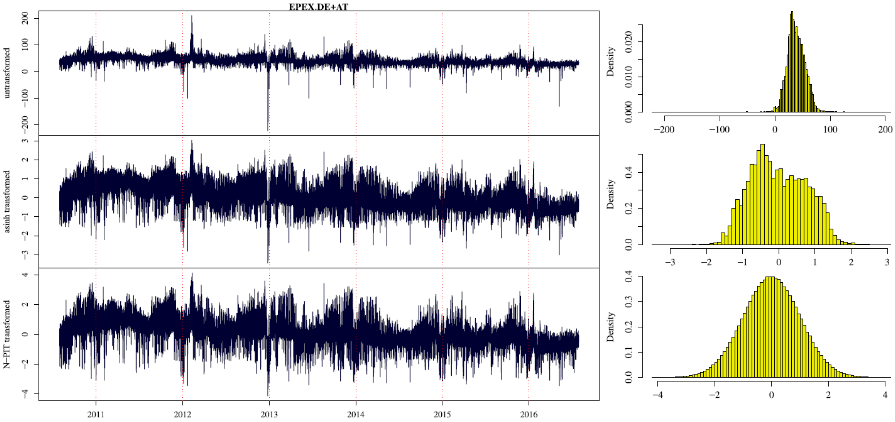


Dealing with asymmetry and heavy tails

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

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

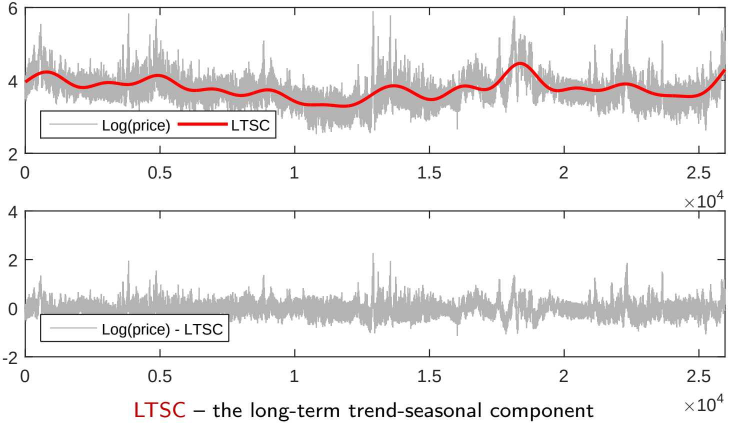
$Y_{d,h} = \text{asinh}(P_{d,h}) \equiv \log(P_{d,h} + \sqrt{P_{d,h}^2 + 1})$ or **(N-)PIT**



What about seasonal decomposition?

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

Decompose → predict the LTSC & residuals → combine



LTSC – the long-term trend-seasonal component

Day-ahead point forecasting: Regression ...

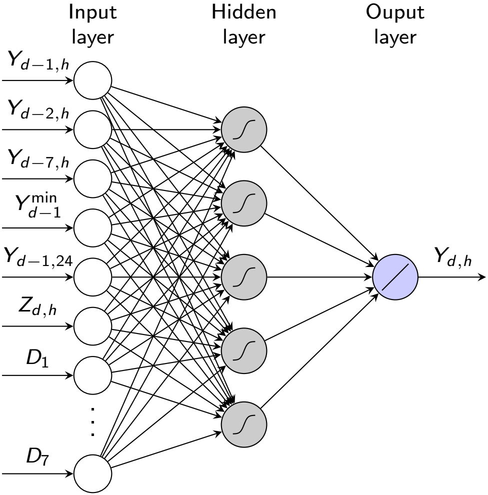
Electricity price for day d and hour h:

$$Y_{d,h} = \underbrace{\beta_{h,1} Y_{d-1,h} + \beta_{h,2} Y_{d-2,h} + \beta_{h,3} Y_{d-7,h}}_{\text{autoregressive terms}}$$

$$+ \underbrace{\beta_{h,4} Y_{d-1}^{\min}}_{\text{non-linear effect}} + \underbrace{\beta_{h,5} Y_{d-1,24}}_{\text{end-of-day effect}} + \underbrace{\beta_{h,6} Z_{d,h}}_{\text{load forecast}}$$

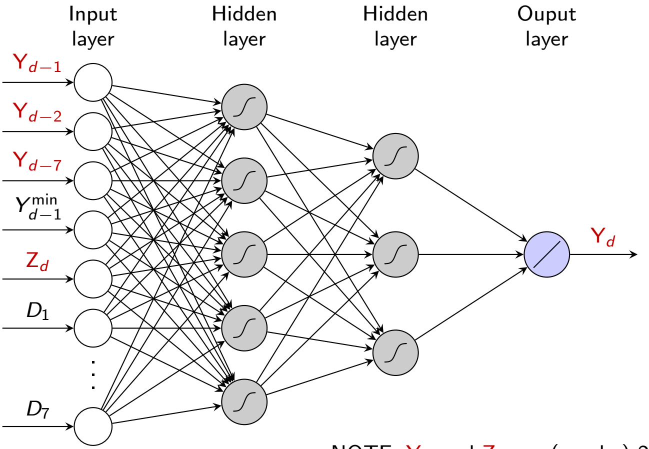
$$+ \underbrace{\sum_{j=1}^{7} \beta_{h,j+6} D_j}_{\text{weekday dummies}} + \varepsilon_{d,h},$$

... neural nets ...



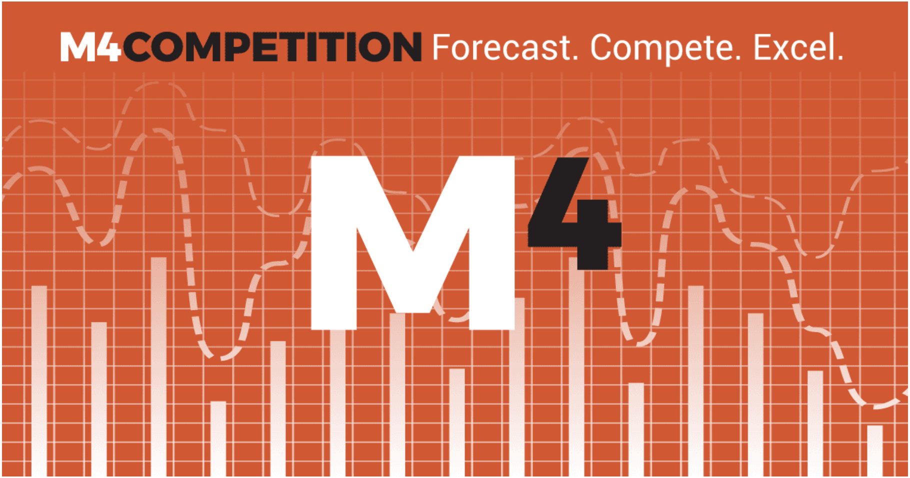
Input layer
Hidden layer
Ouput layer
$Y_{d-1,h}$
$Y_{d-2,h}$
$Y_{d-7,h}$
$Y_{d-1}^{\min}$
$Y_{d-1,24}$
$Z_{d,h}$
D_1
D_7
$Y_{d,h}$

... or deep neural nets (DNN)?



NOTE: Y_d and Z_d are (can be) 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?

Contents lists available at ScienceDirect
Applied Energy
journal homepage: www.elsevier.com/locate/apenergy
ELSEVIER

(2018)

Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms

Jesus Lago[a,b,*], Fjo De Ridder[b], Bart De Schutter[a]
ogy, Mekelweg 2, Delft, The Netherlands
Park, Genk, Belgium

ity prices is proposed.
are statistically significant.
ecasting is presented.
prices are compared.
utperform statistical methods.

Contents lists available at ScienceDirect
International Journal of Forecasting
journal homepage: www.elsevier.com/locate/ijforecast
ELSEVIER

(2019)

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

Grzegorz Marcjasz[a,b], Bartosz Uniejewski[a,b], Rafał Weron[a,*]
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[b] Faculty of Pure and Applied Mathematics, Wrocław University of Science and Technology, Wrocław, Polan

ARTICLE INFO

Keywords:
Electricity spot price
Forecasting
Day-ahead market
Long-term seasonal component
NARX neural network
Committee machine

ABSTRACT

Daily and weekly seasonalities are always
price forecasting, but the long-term seasona
unnecessary complexity, and hence, most st
of the *Seasonal Component AutoRegressive* (S
viewpoint. However, this framework is base
least squares. This paper shows that conside
network-type models with the same inputs
lead to yet better performances. While inc
Network (SCANN) models are generally wo
tures, we provide empirical evidence that c
outperform the latter significantly.

Applied Energy 293 (2021) 116983
Contents lists available at ScienceDirect
Applied Energy
journal homepage: www.elsevier.com/locate/apenergy
ELSEVIER

(2021)

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

Jesus Lago[a,*], Grzegorz Marcjasz[b], Bart De Schutter[a], Rafał Weron[b]
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[b] Department of Operations Research and Business Intelligence, Wrocław University of Science and Technology, Wrocław, Poland

ARTICLE INFO

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

ABSTRACT

OPEN ACCESS

While the field of electricity price forecasting has benefited from plenty of contributions in the last two decades, it arguably lacks a rigorous approach to evaluating new predictive algorithms. The latter are often compared using unique, not publicly available datasets and across too short and limited to one market test samples. The proposed new methods are rarely benchmarked against well established and well performing simpler models, the accuracy metrics are sometimes inadequate and testing the significance of differences in predictive performance is seldom conducted. Consequently, it is not clear which methods perform well nor what are the best practices when forecasting electricity prices. In this paper, we tackle these issues by comparing state-of-the-art statistical and deep learning methods across multiple years and markets, and by putting forward a set of best practices. In addition, we make available the considered datasets, forecasts of the state-of-the-art models, and a specifically designed `python` toolbox, so that new algorithms can be rigorously evaluated in future studies.

Agenda

1. Intro (a bit lengthy)
2. Variable selection
   - LASSO
3. Calibration windows
   - Averaging
   - Identifying breakpoints
4. Beyond point forecasts
   - Probabilistic
   - Path (ensemble)
5. Financial evaluation
   - Trading strategies
   - Euros not errors

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

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

ARTICLE INFO

ABSTRACT

ecasting (EPF) over
aims to explain the
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in the next decade
F studies involving
, and (iii) statistical

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 Operations Research, Wrocław University of Science and Technology, 50-370 Wrocław, Poland

ARTICLE INFO

ABSTRACT

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

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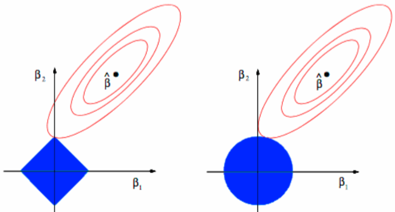
Variable (feature, input) selection using LASSO

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

	h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Day $(d-1)$	$\phi_{h,1,1,0}$	21.42	10.61	9.04	21.81	21.58	11.41	12.62	13.04	12.07	8.86	8.89	8.62	7.10	8.43	6.13	5.93	3.17	0.92	1.63	3.26	4.87	9.18	13.31	19.85
	$\phi_{h,1,2,0}$	41.75	24.36	11.67	4.86	5.44	11.05	16.98	9.80	7.99	6.77	10.67	7.19	6.35	10.08	11.18	10.70	8.47	4.43	4.91	3.58	6.20	5.52	9.19	27.72
	$\phi_{h,1,3,0}$	31.88	39.68	34.41	16.96	9.72	11.60	7.48	2.46	1.29	1.62	1.82	0.64	1.10	2.06	2.39	2.40	4.34	5.21	9.95	10.41	8.36	10.53	10.91	21.31
	$\phi_{h,1,4,0}$	21.50	29.19	39.28	58.20	40.34	11.96	3.39	3.25	4.58	4.36	3.61	2.66	3.26	0.75	0.67	0.25	0.42	1.02	3.02	3.37	2.65	3.66	1.14	9.88
	$\phi_{h,1,5,0}$	32.53	28.35	35.31	51.97	63.97	45.06	13.95	13.64	16.55	15.18	15.80	10.09	11.89	7.81	5.01	3.56	4.77	1.17	1.04	0.74	5.41	7.99	3.39	6.69
	$\phi_{h,1,6,0}$	39.64	41.88	41.60	44.22	54.20	72.06	42.67	20.43	12.95	12.71	6.73	6.12	7.24	4.20	5.07	3.16	2.35	1.75	2.59	2.39	4.03	4.41	1.55	4.67
	$\phi_{h,1,7,0}$	14.67	17.46	10.22	9.48	12.07	19.85	59.92	24.92	14.61	10.70	3.68	7.14	10.71	11.75	10.44	10.80	7.79	7.74	6.96	5.86	6.98	3.43	0.37	0.27
	$\phi_{h,1,8,0}$	10.51	16.08	15.98	16.44	18.32	17.81	19.94	50.14	43.98	15.24	5.71	5.87	6.80	6.71	6.25	7.10	7.60	2.82	2.14	8.68	10.28	4.71	4.77	1.70
	$\phi_{h,1,9,0}$	4.55	3.23	3.04	3.29	3.26	4.73	3.44	10.45	29.03	16.02	6.90	5.66	13.84	13.96	15.17	13.27	20.25	19.73	12.12	7.87	6.27	3.52	3.95	2.94
	$\phi_{h,1,10,0}$	1.06	0.67	1.70	3.14	2.71	4.41	2.55	0.85	6.53	12.52	10.24	4.29	3.46	7.52	10.73	17.44	28.05	29.79	14.38	10.66	5.65	7.72	4.44	3.46
	$\phi_{h,1,11,0}$	9.82	0.19	4.06	3.58	4.56	4.58	1.80	2.58	11.75	19.77	8.90	2.99	0.31	0.00	0.00	0.17	2.62	4.57	3.84	0.54	0.07	0.12	0.41	0.02
	$\phi_{h,1,12,0}$	3.18	0.54	3.59	5.93	12.65	8.56	6.02	2.27	5.97	27.63	33.81	23.73	7.70	1.39	0.61	2.69	6.35	8.62	8.90	6.10	4.08	2.32	2.24	0.15
	$\phi_{h,1,13,0}$	2.61	2.15	2.05	10.61	10.86	5.85	5.27	3.58	4.75	6.53	13.51	25.40	26.51	10.94	3.80	1.42	0.82	3.80	3.62	1.76	1.72	2.51	3.43	2.72
	$\phi_{h,1,14,0}$	8.11	3.18	5.33	6.03	7.05	5.39	6.29	8.75	6.23	16.75	32.36	48.57	55.45	46.23	27.45	8.23	4.38	1.85	2.65	1.00	0.90	2.04	1.39	1.05
	$\phi_{h,1,15,0}$	5.69	5.40	1.01	1.24	1.20	1.04	0.09	5.44	6.44	22.26	30.49	28.40	36.55	43.33	40.31	21.81	4.59	1.32	0.80	0.74	0.61	2.13	1.68	2.46
	$\phi_{h,1,16,0}$	8.71	9.36	5.90	5.94	4.72	14.99	11.28	17.03	23.49	22.16	25.10	30.27	41.13	37.42	45.01	46.93	19.64	6.17	4.26	6.80	4.30	1.24	0.85	5.83
	$\phi_{h,1,17,0}$	15.47	17.07	7.86	5.12	5.31	10.53	10.93	4.56	7.90	8.56	14.35	28.22	35.94	46.70	61.90	69.02	71.11	21.76	5.54	3.82	1.66	1.06	2.20	2.52
	$\phi_{h,1,18,0}$	45.87	38.17	34.61	36.67	38.24	35.07	30.71	26.87	20.60	27.90	36.43	44.84	53.83	60.77	67.40	76.67	96.86	98.27	46.23	11.23	2.72	5.66	6.31	11.48
	$\phi_{h,1,19,0}$	40.18	54.28	61.40	53.42	46.69	49.64	22.85	43.51	39.30	42.98	46.41	32.88	29.82	32.84	25.37	28.45	27.92	67.46	93.92	28.63	4.60	5.87	8.42	19.06
	$\phi_{h,1,20,0}$	26.83	36.61	33.45	23.02	25.11	49.99	63.97	61.77	42.97	41.38	36.44	27.63	28.21	22.75	19.95	19.69	18.18	10.17	43.88	94.59	46.29	7.63	3.84	9.61
	$\phi_{h,1,21,0}$	35.19	31.57	23.84	23.38	23.04	45.30	77.22	69.11	67.79	67.09	63.11	59.66	43.68	42.45	41.45	38.86	35.14	25.28	26.83	51.94	92.74	48.93	11.74	16.59
	$\phi_{h,1,22,0}$	43.63	38.34	39.88	45.70	47.89	50.66	70.33	61.18	68.10	60.56	63.11	64.87	52.10	48.25	47.32	47.90	42.08	27.31	25.42	28.63	75.75	99.17	60.31	32.36
	$\phi_{h,1,23,0}$	30.38	22.55	18.56	18.73	22.85	17.96	25.37	30.99	41.82	50.92	62.93	70.34	65.37	61.04	57.70	56.01	51.60	46.40	38.14	37.16	32.31	63.60	95.44	68.07
	$\phi_{h,1,24,0}$	100	100	100	100	100	100	99.99	96.41	94.71	93.01	91.30	90.15	92.68	93.25	95.27	95.59	91.48	90.29	87.18	77.23	77.69	81.20	90.89	100
Day $(d-2)$	$\phi_{h,2,1,0}$	15.84	1.79	4.21	5.25	5.34	3.34	3.83	5.68	6.57	8.00	10.54	10.66	8.02	11.72	11.28	11.46	14.86	11.63	9.81	6.47	7.57	17.03	12.15	32.15
	$\phi_{h,2,2,0}$	11.33	11.67	7.23	5.03	4.41	6.66	12.34	6.97	4.28	5.55	4.67	5.33	8.32	8.02	7.12	5.63	4.00	6.00	5.11	3.81	3.23	3.82	2.50	10.75
	$\phi_{h,2,3,0}$	6.16	19.18	16.01	5.20	3.99	12.08	14.63	12.38	13.78	9.46	5.96	5.47	6.82	7.90	7.75	9.05	9.76	8.52	7.94	4.85	5.64	3.63	1.80	5.23
	$\phi_{h,2,4,0}$	7.46	7.07	17.57	28.57	20.01	20.24	15.02	14.12	10.38	4.21	4.35	2.68	2.03	7.60	9.97	8.58	5.64	5.61	5.57	2.74	2.69	2.10	0.26	1.05
	$\phi_{h,2,5,0}$	28.03	22.72	22.68	31.32	44.40	26.97	23.42	20.64	17.51	13.66	7.71	3.55	6.29	5.84	8.70	8.59	6.37	5.43	6.28	1.62	0.25	2.31	4.53	6.02
	$\phi_{h,2,6,0}$	5.56	12.60	6.95	7.92	8.61	17.33	19.61	14.77	8.82	7.02	8.17	8.44	9.15	8.67	5.67	5.31	5.11	4.59	6.25	5.51	6.62	4.47	3.62	2.76
	$\phi_{h,2,7,0}$	7.69	7.04	6.93	9.31	7.69	5.55	13.85	10.65	5.23	1.87	2.63	2.86	6.14	7.68	5.06	3.25	3.08	0.70	0.50	2.54	0.89	0.49	1.06	3.11
	$\phi_{h,2,8,0}$	3.06	4.69	9.56	8.40	10.46	14.53	7.63	6.42	3.82	3.07	3.20	6.65	11.17	10.39	11.62	12.43	12.32	10.38	4.77	4.20	2.95	5.24	3.71	2.50
	$\phi_{h,2,9,0}$	4.38	4.91	6.96	7.16	4.28	6.49	0.88	0.83	2.22	0.50	0.13	0.22	0.25	2.50	5.54	9.77	16.26	18.22	13.66	14.32	6.20	3.02	6.17	8.61
	$\phi_{h,2,10,0}$	0.58	3.38	9.78	12.23	8.61	8.68	2.64	4.91	6.27	8.20	1.41	0.90	0.71	1.51	1.19	3.80	6.17	8.54	5.95	4.83	2.51	1.85	0.35	0.29
	$\phi_{h,2,11,0}$	4.12	5.40	6.54	8.88	5.96	7.08	0.78	2.43	4.39	8.82	7.44	2.22	0.91	0.92	0.83	2.70	4.55	6.91	10.88	9.55	4.27	0.87	1.10	1.12
	$\phi_{h,2,12,0}$	2.87	7.99	10.28	16.54	15.03	8.20	2.49	3.39	2.09	5.72	10.04	4.87	0.77	0.07	0.14	0.03	0.08	1.01	2.95	2.84	4.55	1.37	2.40	2.96
	$\phi_{h,2,13,0}$	1.60	2.15	7.18	9.78	9.10	8.91	9.30	4.47	2.52	3.00	9.57	16.71	20.59	10.52	8.47	5.60	2.31	4.66	10.47	7.13	2.42	0.82	4.37	2.99
	$\phi_{h,2,14,0}$	0.34	3.70	4.58	5.43	7.52	6.51	2.43	2.35	1.31	1.12	2.02	3.82	5.66	5.38	3.44	0.63	0.21	3.03	3.84	5.05	3.62	0.74	0.01	0.40
	$\phi_{h,2,15,0}$	0.53	2.00	7.82	8.78	11.00	8.52	15.17	12.04	5.29	1.82	2.79	8.16	9.21	7.86	5.62	0.28	0.42	6.18	2.34	6.29	1.78	2.78	0.22	2.90
	$\phi_{h,2,16,0}$	2.25	3.88	5.04	6.00	7.62	7.56	1.89	4.49	2.91	2.73	1.85	4.04	4.37	5.83	5.29	8.06	5.37	12.93	12.28	6.63	1.72	3.06	2.85	12.53
	$\phi_{h,2,17,0}$	1.87	2.68	8.77	10.66	15.49	9.29	1.75	4.29	7.67	8.33	1.10	1.99	6.61	8.02	14.35	19.60	22.91	10.93	5.91	1.53	0.50	0.47	0.96	3.47
	$\phi_{h,2,18,0}$	0.45	5.17	7.79	6.99	7.79	6.17	6.30	6.01	1.53	1.50	2.35	4.88	14.11	16.96	23.02	35.14	55.58	71.47	19.41	2.91	0.60	1.75	3.62	6.15
	$\phi_{h,2,19,0}$	1.13	0.78	1.21	0.59	0.90	2.40	0.99	2.20	1.07	0.86	1.85	8.21	9.90	11.38	11.78	15.90	20.69	22.86	65.00	7.55	10.46	2.90	3.92	4.87
	$\phi_{h,2,20,0}$	8.56	3.10	4.47	4.71	6.34	2.30	8.83	8.58	4.52	3.57	3.77	9.78	13.00	14.00	13.53	15.40	13.24	13.86	15.47	78.76	18.60	12.22	15.66	16.72
	$\phi_{h,2,21,0}$	10.20	15.79	20.62	28.96	26.19	13.22	9.92	18.27	3.90	9.20	9.18	7.61	8.50	15.20	15.75	13.42	10.50	9.22	8.66	20.05	70.64	18.09	11.22	8.16
	$\phi_{h,2,22,0}$	17.33	31.56	25.33	22.22	18.10	15.44	7.23	8.50	1.41	0.87	2.39	6.00	2.21	1.54	5.28	6.41	5.99	3.83	1.45	6.88	6.76	57.21	24.05	5.87
	$\phi_{h,2,23,0}$	21.07	25.48	36.76	34.48	41.17	42.37	25.07	18.53	14.87	11.26	14.30	13.81	9.53	9.50	7.35	7.67	12.92	6.47	5.57	6.29	9.65	13.14	49.49	30.34
	$\phi_{h,2,24,0}$	14.67	14.58	24.65	33.56	34.54	25.40	16.97	16.40	12.55	10.68	10.74	11.94	22.76	19.63	15.06	14.10	9.93	2.97	7.17	12.21	14.60	27.42	38.10	54.77
Day $(d-3)$	$\phi_{h,3,1,0}$	6.76	4.68	5.62	8.37	9.62	6.95	12.04	4.02	5.48	5.87	3.20	4.20	4.75	6.05	5.69	7.44	6.69	3.50	5.22	4.71	4.83	6.12	6.56	21.20
	$\phi_{h,3,2,0}$	6.71	6.10	4.81	1.07	0.17	3.75	4.57	9.02	8.90	6.80	8.74	9.71	8.63	12.30	9.25	10.05	11.82	8.93	9.36	2.98	5.10	8.73	10.69	16.67
	$\phi_{h,3,3,0}$	9.07	16.58	10.43	3.99	1.45	2.82	2.76	2.82	2.61	1.22	0.74	2.87	3.20	2.54	2.06	1.33	2.04	0.61	0.79	0.90	1.29	1.12	4.29	1.71
	$\phi_{h,3,4,0}$	11.31	16.38	24.62	25.34	29.17	24.38	9.08	7.18	1.13	3.04	2.11	2.52	4.20	4.14	5.01	2.93	5.00	2.91	2.68	0.34	2.51	0.53	1.22	1.86
	$\phi_{h,3,5,0}$	7.51	5.12	5.18	11.50	13.86	10.25	4.71	4.42	2.25	3.15	3.46	6.39	6.50	2.19	4.91	4.63	6.75	5.63	6.11	3.54	1.71	0.69	0.52	1.79
	$\phi_{h,3,6,0}$	13.44	5.62	5.04	10.06	11.01	24.92	7.88	3.92	5.14	5.53	3.90	5.35	4.41	3.86	3.85	5.16	7.73	10.25	6.99	3.58	3.67	4.78	3.50	2.63
	$\phi_{h,3,7,0}$	14.88	15.06	22.54	21.76	17.35	15.99	24.22	20.67	17.07	14.44	11.17	9.17	3.54	3.58	5.84	4.86	4.48	10.15	9.30	16.67	4.84	2.52	0.84	1.69
	$\phi_{h,3,8,0}$	2.08	5.13	6.03	8.81	3.08	1.13	4.88	9.29	3.95	2.60	1.28	0.58	0.11	0.18	2.14	2.79	3.34	1.53	2.32	2.19	2.29	1.57	3.82	1.81
	$\phi_{h,3,9,0}$	2.95	3.12	1.51	5.82	4.95	2.60	1.45	8.35	11.09	5.59	2.15	1.59	0.71	0.49	1.80	3.25	5.84	8.81	7.98	7.24	6.00	5.61	4.56	4.46
	$\phi_{h,3,10,0}$	4.74	7.72	2.39	2.12	0.76	0.61	0.82	5.03	9.25	8.54	5.29	1.84	0.76	0.38	2.64	3.20	2.93	4.66	3.88	3.67	5.40	3.38	3.78	7.51
	$\phi_{h,3,11,0}$	2.71	0.50	1.67	2.93	3.18	3.77	7.27	12.10	4.69	6.89	6.04	2.51	0.08	2.90	3.18	1.04	0.91	2.49	1.58	1.63	0.49	0.31	0.49	1.09
	$\phi_{h,3,12,0}$	0.95	2.48	2.33	2.80	3.99	7.35	2.23	0.57	1.34	3.40	6.99	12.17	7.93	3.26	2.52	3.32	2.12	1.64	3.67	3.69	1.50	0.61	0.92	3.07
	$\phi_{h,3,13,0}$	1.51	0.77	1.83	3.64	4.05	2.26	2.06	1.21	1.35	5.31	8.46	17.77	25.33	16.77	8.93	6.91	5.25	0.92	0.06	2.53	1.20	0.49	2.56	4.59
	$\phi_{h,3,14,0}$	2.09	1.48	2.70	4.38	6.91	6.25	5.37	3.13	3.46	0.21	0.31	4.82	7.43	6.88	5.60	3.29	2.32	2.27	0.58	1.29	2.96	0.93	2.35	5.52
	$\phi_{h,3,15,0}$	0.18	1.83	1.13	2.36	3.11	3.55	4.05	3.76	5.32	0.71	0.34	0.13	0.29	4.58	9.83	12.53	5.95	6.97	8.04	3.82	2.68	2.76	3.18	6.47
	$\phi_{h,3,16,0}$	3.33	3.45	5.66	7.45	12.35	5.57	2.80	2.70	3.26	1.92	0.62	0.55	0.44	1.27	2.96	7.10	0.25	0.57	4.34	5.17	2.96	5.56	4.21	2.19
	$\phi_{h,3,17,0}$	0.55	0.65	6.17	8.98	11.99	12.71	15.72	12.11	15.58	15.59	7.68	4.72	5.74	9.33	9.37	7.54	18.29	7.02	6.31	7.39	3.89	2.39	2.46	0.59
	$\phi_{h,3,18,0}$	4.20	1.31	3.42	3.02	3.20	1.92	0.53	1.33	0.87	2.22	8.35	4.44	9.65	9.77	13.13	16.15	26.09	43.75	11.98	0.84	1.38	4.57	3.18	1.88
	$\phi_{h,3,19,0}$	3.68	3.48	4.53	3.18	3.07	4.96	4.24	0.47	0.07	2.25	5.67	5.29	5.11	2.04	1.43	1.25	3.92	11.59	46.20	7.92	1.84	4.00	3.25	3.54
	$\phi_{h,3,20,0}$	3.02	1.09	0.79	2.69	2.05	3.38	7.04	2.56	1.78	2.44	1.25	0.61	2.79	0.74	1.12	1.42	2.56	1.33	1.87	46.83	11.70	0.65	0.82	1.66
	$\phi_{h,3,21,0}$	5.73	3.04	4.21	7.49	7.74	2.76	18.60	11.10	6.76	2.87	1.35	2.77	3.19	1.88	4.40	2.58	5.53	3.78	2.71	8.09	34.61	6.37	2.49	1.03
	$\phi_{h,3,22,0}$	3.90	8.02	5.68	7.28	9.30	1.82	2.31	4.21	5.82	3.29	0.87	2.37	2.75	3.94	7.44	5.71	8.61	12.19	14.01	2.47	4.59	21.98	3.95	3.08
	$\phi_{h,3,23,0}$	5.57	14.75	16.49	16.00	12.54	8.54	4.50	2.11	3.83	4.15	7.82	4.86	4.80	3.53	3.24	5.44	4.35	4.63	7.63	8.56	4.66	11.53	29.60	12.28
	$\phi_{h,3,24,0}$	2.56	4.32	10.43	13.79	11.89	7.55	4.66	9.26	3.64	3.13	6.52	11.26	11.33	8.73	7.67	6.34	8.65	5.25	3.51	2.12	4.19	9.10	17.41	41.48

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

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



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

Red ellipses – contours of the LS error function

Agenda

1. Intro (a bit lengthy)
2. Variable selection
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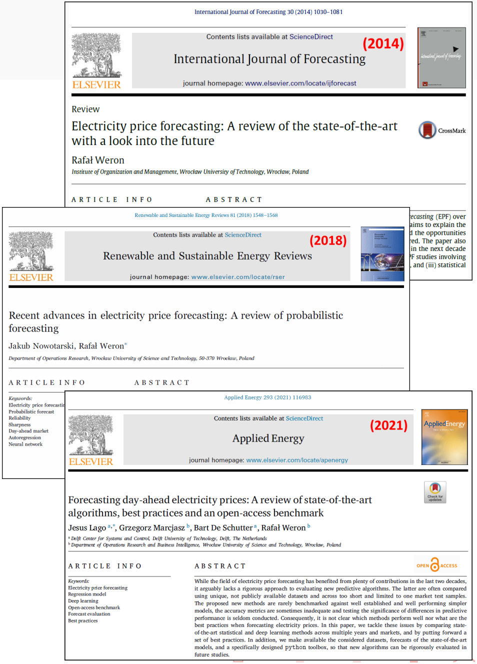
   - Probabilistic
   - Path (ensemble)
5. Financial evaluation
   - Trading strategies
   - Euros not errors



International Journal of Forecasting 30 (2014) 1030–1081

Contents lists available at ScienceDirect

(2014)

International Journal of Forecasting

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

Review

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

Rafał Weron

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

ARTICLE INFO

ABSTRACT

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

Contents lists available at ScienceDirect

(2018)

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

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

Jakub Nowotarski, Rafał Weron*

Department of Operations Research, Wrocław University of Science and Technology, 50-370 Wrocław, Poland

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ABSTRACT

Applied Energy 293 (2021) 116983

Contents lists available at ScienceDirect

(2021)

Applied Energy

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

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

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

[a] Delft Center for Systems and Control, Delft University of Technology, Delft, The Netherlands

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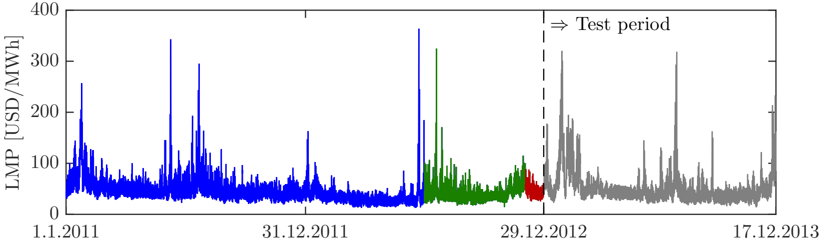
ARTICLE INFO

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 contributions in the last two decades, it arguably lacks a rigorous approach to evaluating new predictive algorithms. The latter are often compared using unique, not publicly available datasets and across too short and limited to one market test samples. The proposed new methods are rarely benchmarked against well established and well performing simpler models, the accuracy metrics are sometimes inadequate and testing the significance of differences in predictive performance is seldom conducted. Consequently, it is not clear which methods perform well nor what are the best practices when forecasting electricity prices. In this paper, we tackle these issues by comparing state-of-the-art statistical and deep learning methods across multiple years and markets, and by putting forward a set of best practices. In addition, we make available the considered datasets, forecasts of the state-of-the-art models, and a specifically designed python toolbox, so that new algorithms can be rigorously evaluated in future studies.

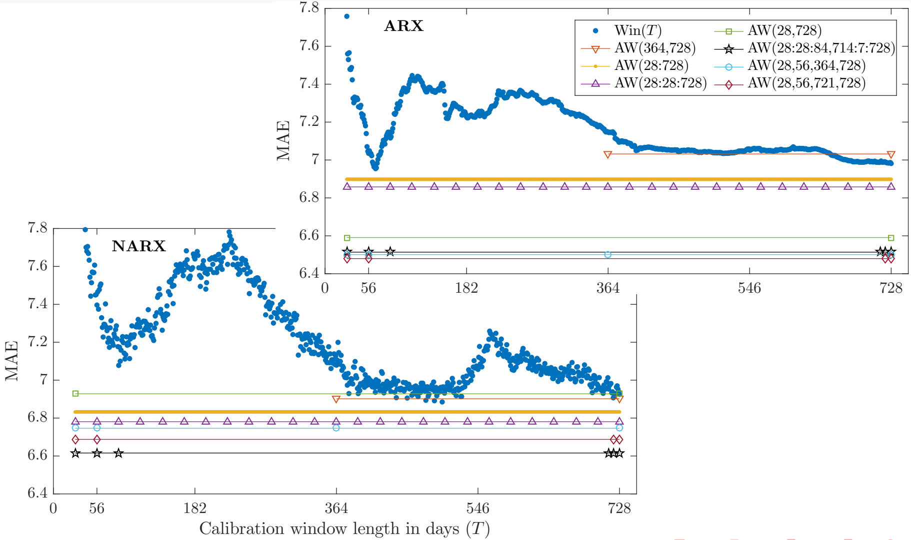
Searching for the optimal calibration window



- 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
- Typically selected ad-hoc
  - Ranging from 10 days to 6 years

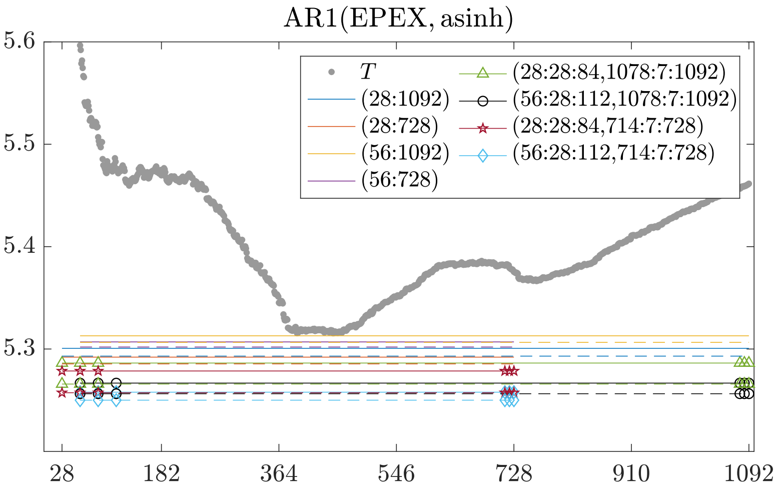
Averaging across calibration windows

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

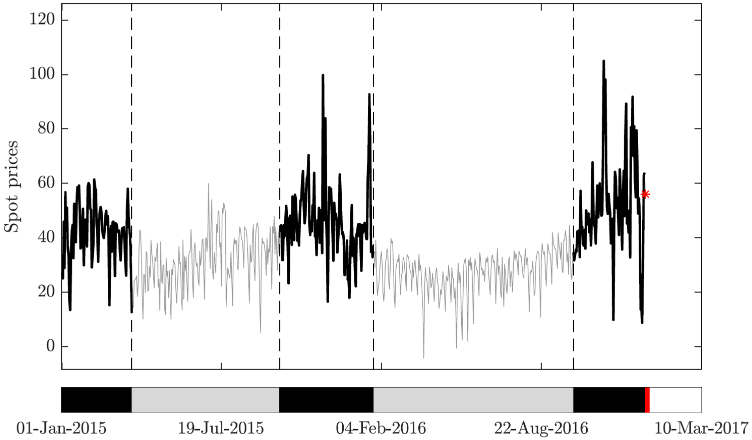


Past performance-weighted averaging

(Marcjasz, Serafin & Weron, 2018, Energies) '—' AW, '- -' WAW

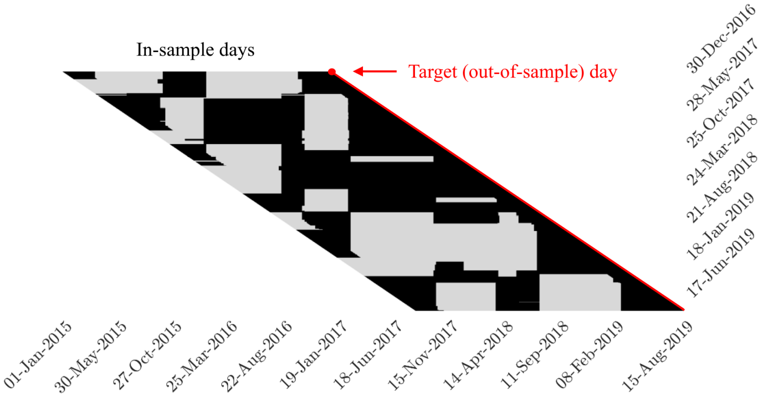


Detection of change/breakpoints



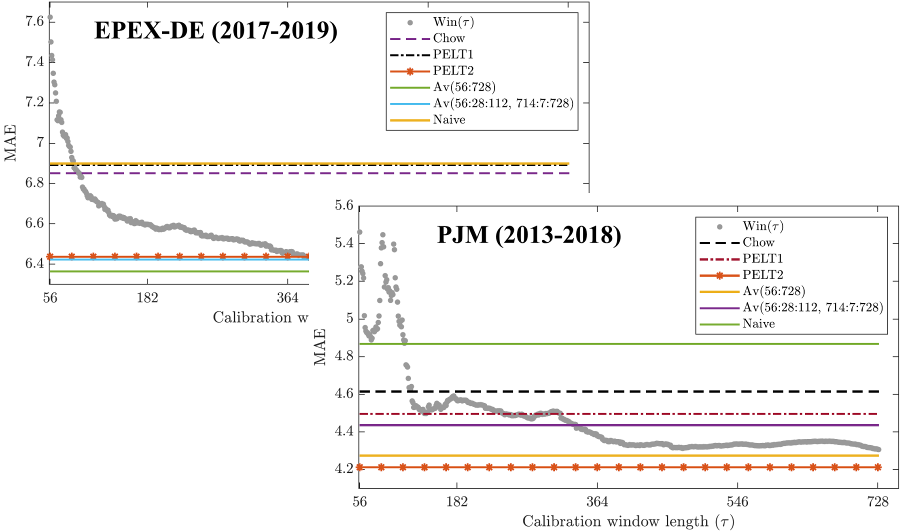
EPEX-DE 18h: Pruned Exact Linear Time (PELT)

PELT: Killick et al. (2012, JASA); EPF: Kaszuba (2020, MSc)



EPEX-DE and PJM: MAE errors

(Kaszuba, 2020, MSc)



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Probabilistic forecast
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

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*

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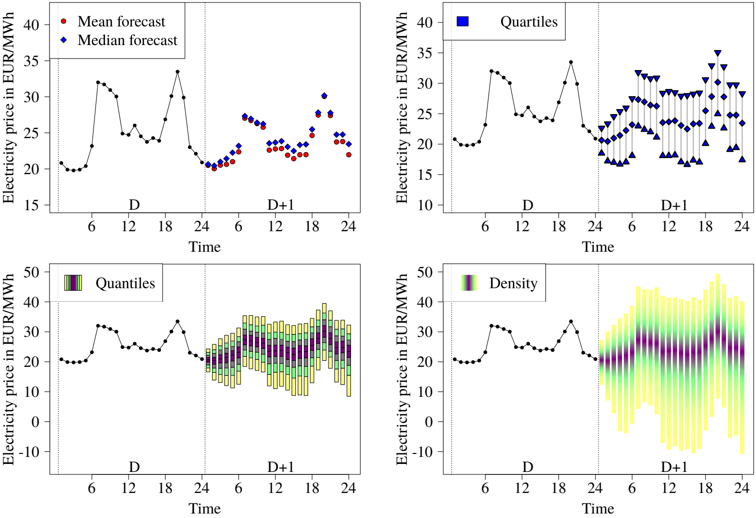
OPEN ACCESS

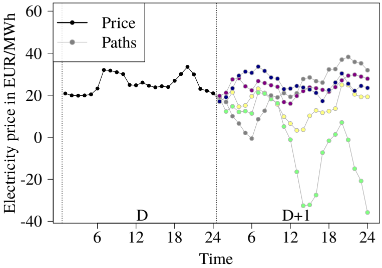
While the field of electricity price forecasting has benefited from plenty of contributions in the last two decades, it arguably lacks a rigorous approach to evaluating new predictive algorithms. The latter are often compared using unique, not publicly available datasets and across too short and limited to one market test samples. The proposed new methods are rarely benchmarked against well established and well performing simpler models, the accuracy metrics are sometimes inadequate and testing the significance of differences in predictive performance is seldom conducted. Consequently, it is not clear which methods perform well nor what are the best practices when forecasting electricity prices. In this paper, we tackle these issues by comparing state-of-the-art statistical and deep learning methods across multiple years and markets, and by putting forward a set of best practices. In addition, we make available the considered datasets, forecasts of the state-of-the-art models, and a specifically designed python toolbox, so that new algorithms can be rigorously evaluated in future studies.

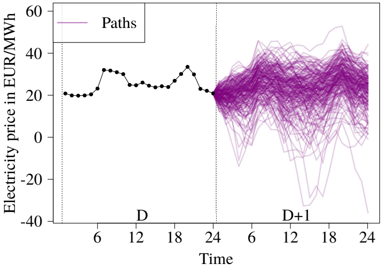
A new hype: Point → probabilistic forecasting

(ca. 7% of EPF papers)



Not yet a hype: Probabilistic → 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

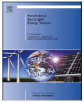
Recent reviews of probabilistic EPF

Contents lists available at ScienceDirect

(2018)

Renewable and Sustainable Energy Reviews

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



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

Jakub Nowotarski, Rafał Weron*

Department of Operations Research, Wrocław University of Science and Technology, 50-370 Wrocław, Poland

A R T I C L E I N F O

Keywords:
Electricity price forecasting
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Reliability
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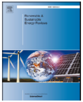


Probabilistic mid- and long-term electricity price forecasting

Florian Ziel[a,*], Rick Steinert[b]

[a] *Universität Duisburg-Essen, Berliner Platz 6-8, 45127 Essen, Germany*
[b] *Europa-Universität Viadrina, Große Scharrnstraße 59, 15230 Frankfurt, Oder, Germany*

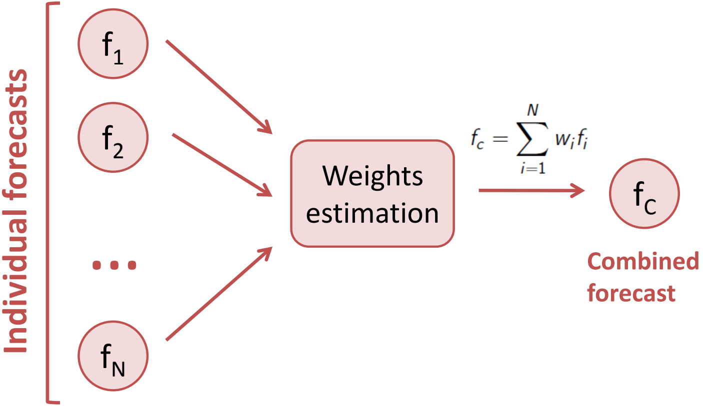
A R T I C L E I N F O

Keywords:
Electricity prices
Probabilistic forecasting

A B S T R A C T

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 electricity price movements. The increasing amount of papers, which aim to model and predict electricity prices

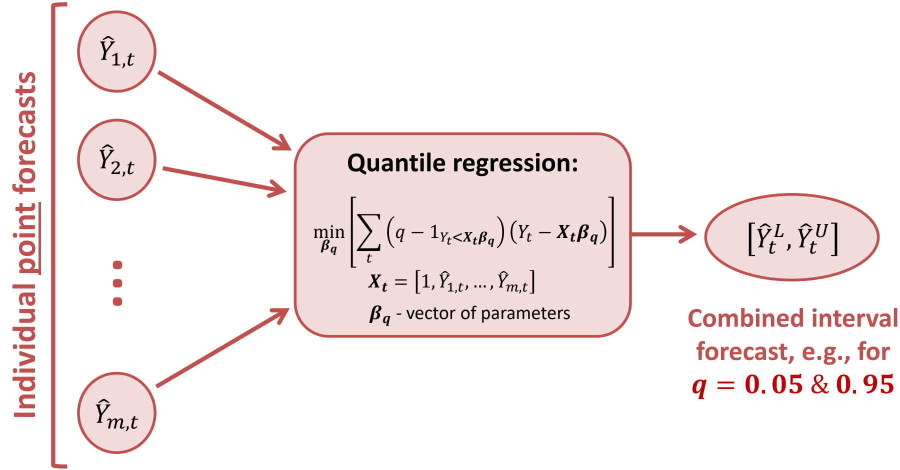
Point forecast averaging: The idea



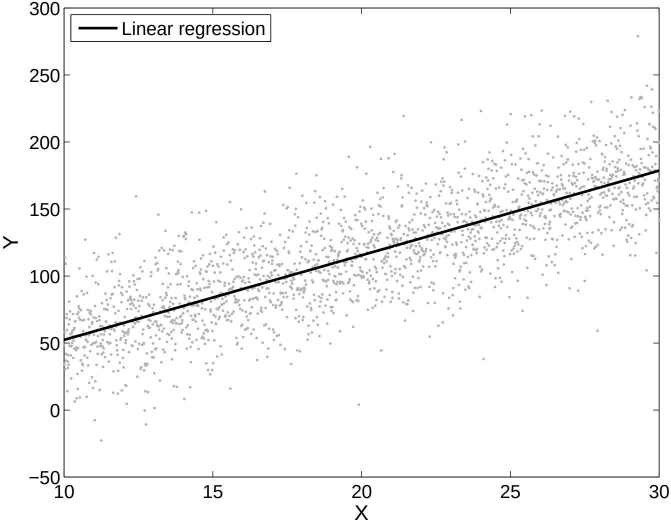
- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger

Quantile Regression Averaging: The idea

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



Quantile regression



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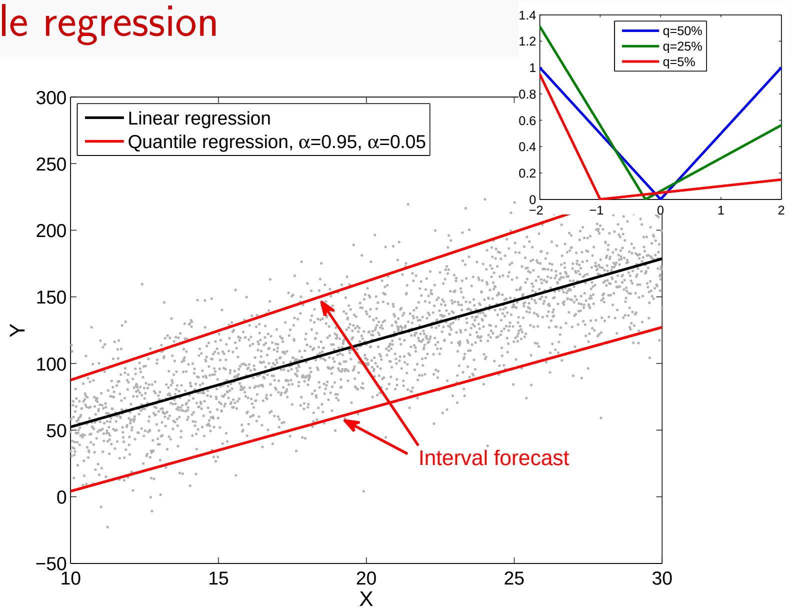
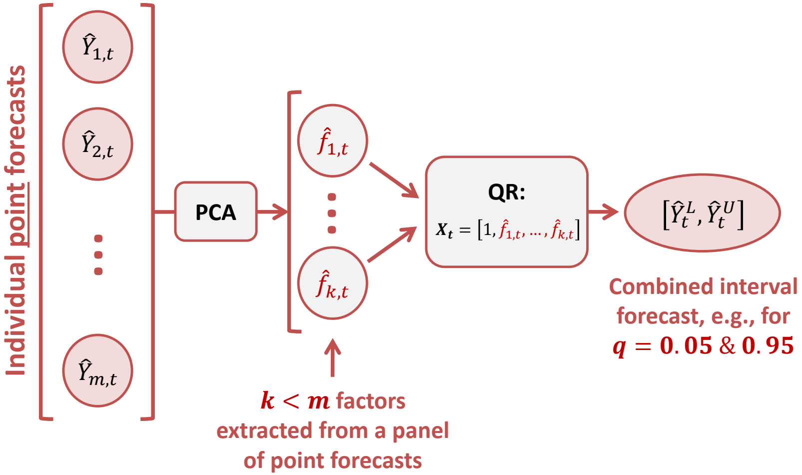


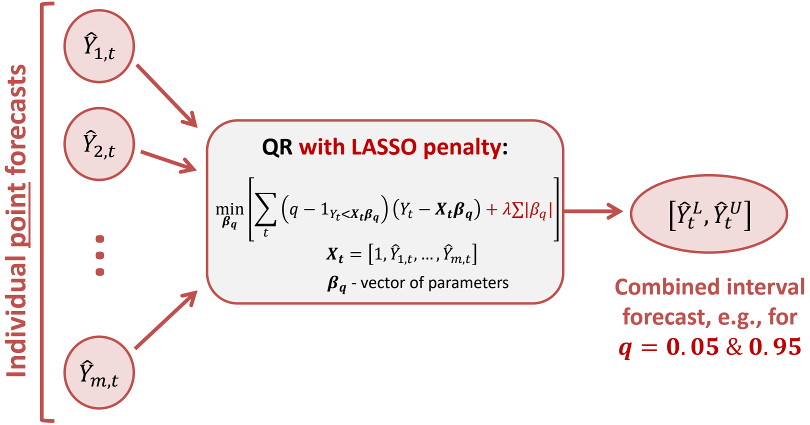
FQRA: When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



LASSO QRA (LQRA): An alternative to FQRA

(Uniejewski & Weron, 2021, ENEECO)



Agenda

1. Intro (a bit lengthy)
2. Variable selection
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3. Calibration windows
   - Averaging
   - Identifying breakpoints
4. Beyond point forecasts
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International Journal of Forecasting 30 (2014) 1030–1081

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ELSEVIER

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

Check for updates

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

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

ARTICLE INFO

Keywords:
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Economic/financial impact of forecasting errors

(2010)

IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 25, NO. 1, FEBRUARY 2010

Economic Impact of Electricity Market Price Forecasting Errors: A Demand-Side Analysis

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

***Abstract*—Several techniques have been proposed in the literature to forecast electricity market prices and improve forecast accuracy. However, no studies have been reported examining the economic impact of price forecast inaccuracies on forecast users. Therefore, in this paper, the application of electricity market price forecasts to short-term operation scheduling of two typical and inherently different industrial loads is examined and the associated economic impact is analyzed. Using electricity market price forecasts as the expected next-day electricity prices, optimal operating schedules and the associated costs are determined for each load. These costs are compared with those of a "perfect" price forecast scenario in which actual prices are used to determine the operating schedules. Numerical results and discussions are provided based on price forecasts with different error characteristics.**

***Index Terms*—Demand-side management, economic benefit, economic value, forecasting error, price forecasting, scheduling.**

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ELSEVIER

Energy Economics

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The value of forecasts: Quantifying the economic gains of accurate quarter-hourly electricity price forecasts

Check for updates

Christopher Kath[a,*,1], Florian Ziel[b]

[a] RWE Supply & Trading GmbH, Altenessenerstr. 27, Essen 45141, Germany
[b] University Duisburg-Essen, House of Energy Markets and Finance, Germany

energies

(2020) MDPI

Article

Balancing Generation from Renewable Energy Sources: Profitability of an Energy Trader

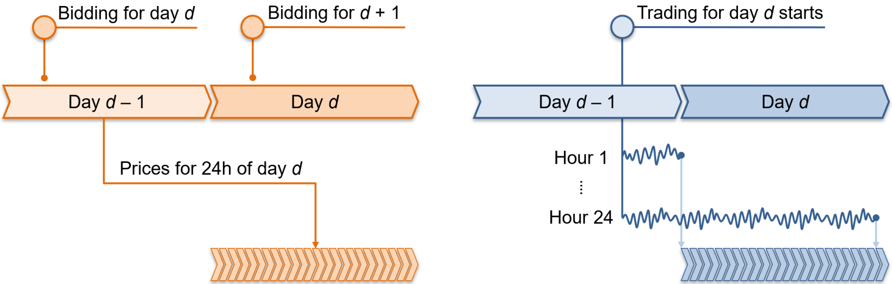
Christopher Kath [1,2], Weronika Nitka [3,4], Tomasz Serafin [3,4], Tomasz Weron [3,4], Przemysław Zaleski [3,5] and Rafał Weron [3,*]

1 RWE Supply & Trading GmbH, 45141 Essen, Germany; christopher.kath@rwe.com
2 House of Energy Markets and Finance, University of Duisburg-Essen, 45141 Essen, Germany
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@gmail.com (T.W.); przemyslaw.zaleski@pwr.edu.pl (P.Z.)

net regression forecast model for German quarter-hourly electricity spot
verse on day-ahead prediction approaches, both the intraday continuous
ave not been studied intensively with a clear focus on predictive power.
g, we check for the impact of early day-ahead (DA) EXAA prices on intra-
his paper is the complementary discussion of economic benefits. A precise
be utilized. We elaborate possible trading decisions based upon our fore-
monetary effects. We find that even simple electricity trading strategies
mpact if combined with a decent forecasting technique.

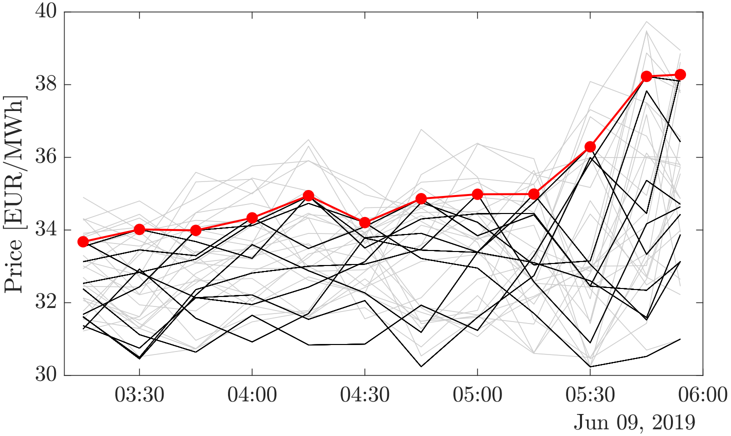
Day-ahead vs. intraday markets

Auction vs. continuous trading



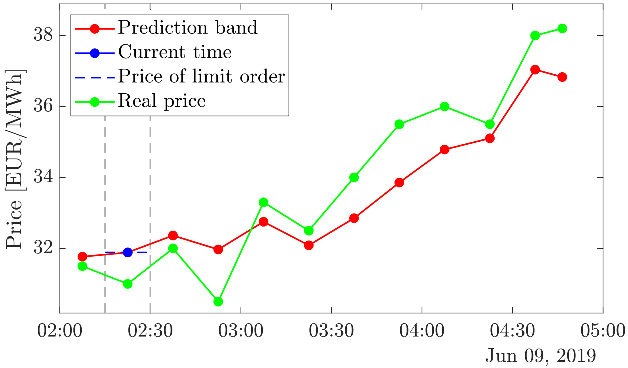
Forecast price paths → set prediction bands

(Serafin, Marcjasz & Weron, 2020, WP)



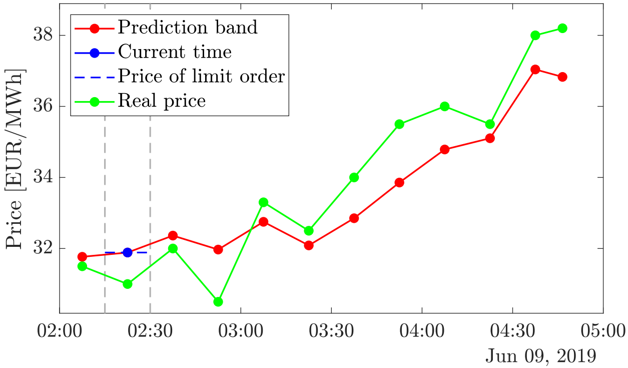
Prediction band-based trading strategy

- The prediction band determines the price of the *limit order* which is placed in the market every 15 minutes



Prediction band-based trading strategy

- If the order is not filled, the limit order is modified to match the next value of the prediction band



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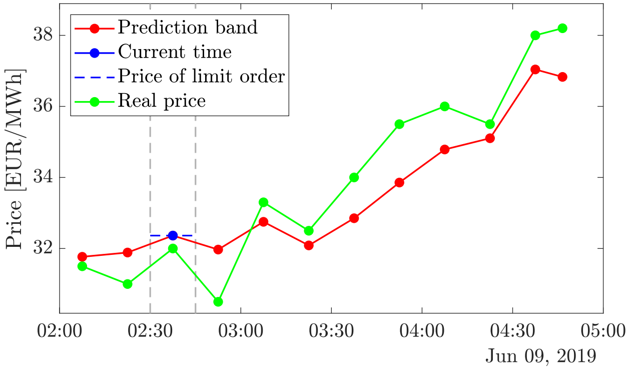

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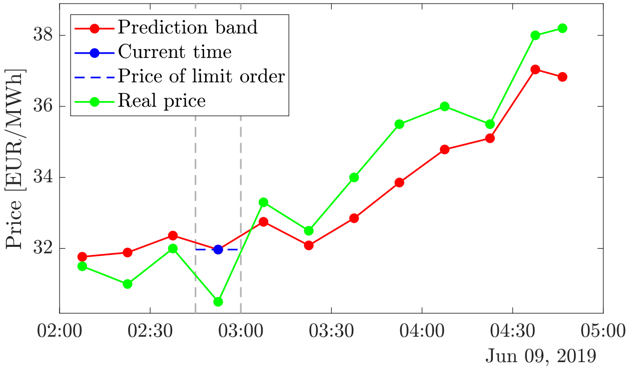
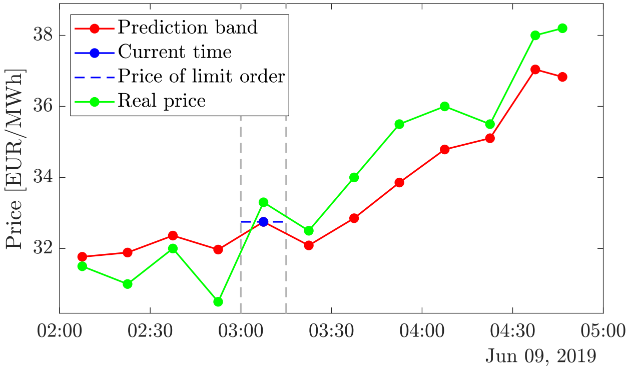


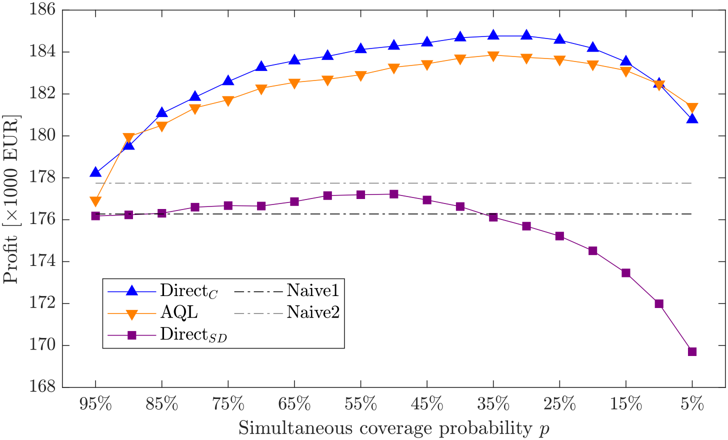
Prediction band-based trading strategy

- If none of the orders was filled, the electricity is sold at the last price in the market



Profits

Total profit from selling 1 MWh of electricity every hour of the 200-day out-of-sample period:



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