Recent advances in electricity price forecasting (EPF)

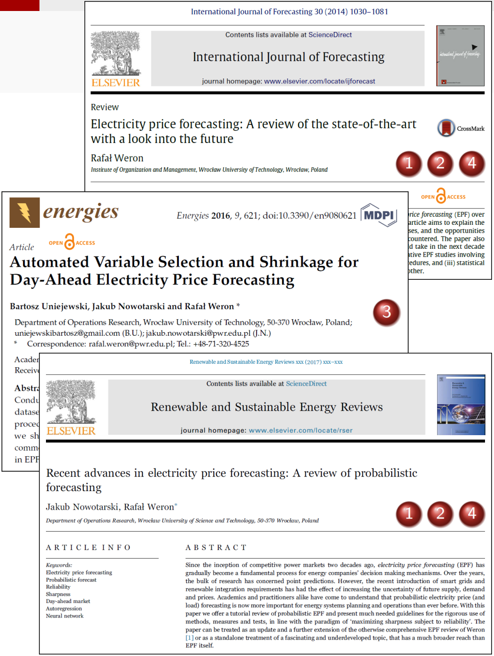
Rafał Weron

Department of Operations Research
Wrocław University of Science and Technology, Poland

http://www.ioz.pwr.wroc.pl/pracownicy/weron/

Agenda

1. Beyond point forecasts $\Rightarrow$ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Variable selection and shrinkage
   - LASSO
   - Elastic nets
4. Guidelines for evaluating forecasts



A new book on EPF ... forthcoming in 2018

Rafał Weron, Florian Ziel

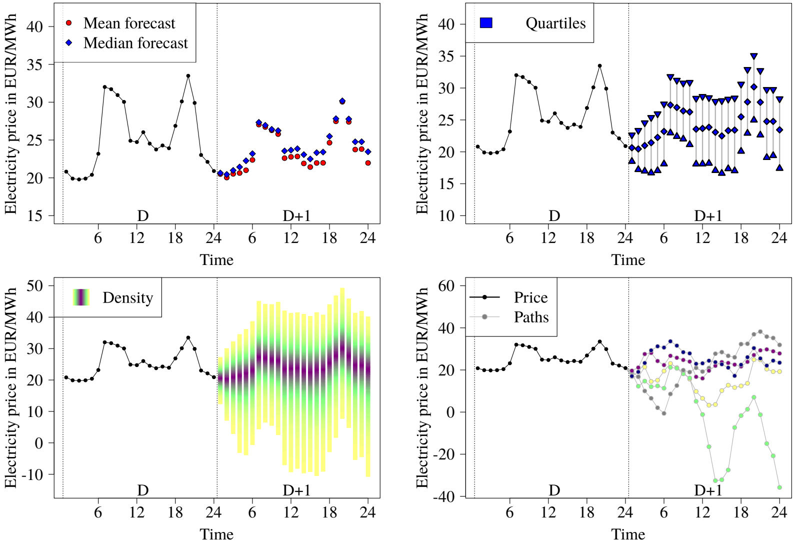
CRC Press
Taylor & Francis Group

Forecasting Electricity Prices: A Guide to Robust Modeling

Chapters:

1. The Art of Forecasting
2. Markets for Electricity
3. Forecasting for Beginners
4. Evaluating Models and Forecasts
5. Forecasting for Experts

Point → probabilistic → path forecasting



A (very) recent review of probabilistic forecasting

Renewable and Sustainable Energy Reviews xxx (2017) xxx–xxx

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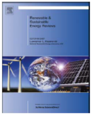
Renewable and Sustainable Energy Reviews

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

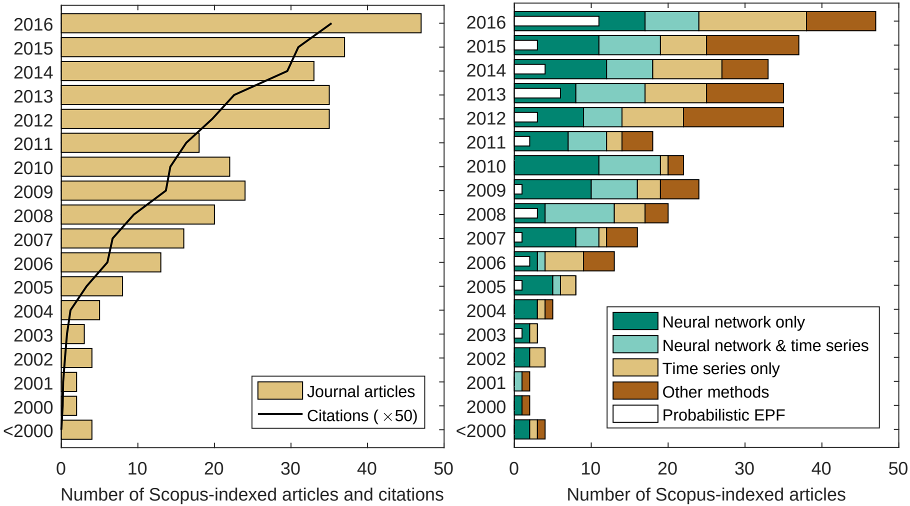
A R T I C L E I N F O

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

A B S T R A C T

Since the inception of competitive power markets two decades ago, *electricity price forecasting* (EPF) has gradually become a fundamental process for energy companies' decision making mechanisms. Over the years, the bulk of research has concerned point predictions. However, the recent introduction of smart grids and renewable integration requirements has had the effect of increasing the uncertainty of future supply, demand and prices. Academics and practitioners alike have come to understand that probabilistic electricity price (and load) forecasting is now more important for energy systems planning and operations than ever before. With this paper we offer a tutorial review of probabilistic EPF and present much needed guidelines for the rigorous use of methods, measures and tests, in line with the paradigm of 'maximizing sharpness subject to reliability'. The paper can be treated as an update and a further extension of the otherwise comprehensive EPF review of Weron [1] or as a standalone treatment of a fascinating and underdeveloped topic, that has a much broader reach than EPF itself.

Papers, cites



GEFCom2014

(Hong, Pinson, Fan et al., 2016, IJF)

GEFCOM 2014 Load Forecasting
GEFCOM 2014 Price Forecasting
GEFCOM 2014 Wind Forecasting
GEFCOM 2014 Solar Forecasting
IEEE PES Power & Energy Society®

- Incremental data sets released on weekly basis
- Price Track:
  - 287 contestants
  - Submit 99 quantiles for 24h load periods of the next day

Price Track: Top winning teams

(1st and) 2nd place for QRA!

1. Pierre Gaillard, Yannig Goude, Raphaël Nedellec (EDF R&D, F)
2. Katarzyna Maciejowska, Jakub Nowotarski (Wrocław UT, PL)
3. Grzegorz Dudek (Częstochowa UT, PL)
4. Zico Kolter, Romain Juban, Henrik Ohlsson, Mehdi Maasoumy (C3 Energy, USA)
5. Frank Lemke (KnowledgeMiner Software, D)

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

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other.

energies
Energies 2016, 9, 621; doi:10.3390/en9080621

Article

Automated Variable Selection and Shrinkage for Day-Ahead Electricity Price Forecasting

Bartosz Uniejewski, Jakub Nowotarski and Rafał Weron *
Department of Operations Research, Wrocław University of Technology, 50-370 Wrocław, Poland; uniejewskibartosz@gmail.com (B.U.); jakub.nowotarski@pwr.edu.pl (J.N.)
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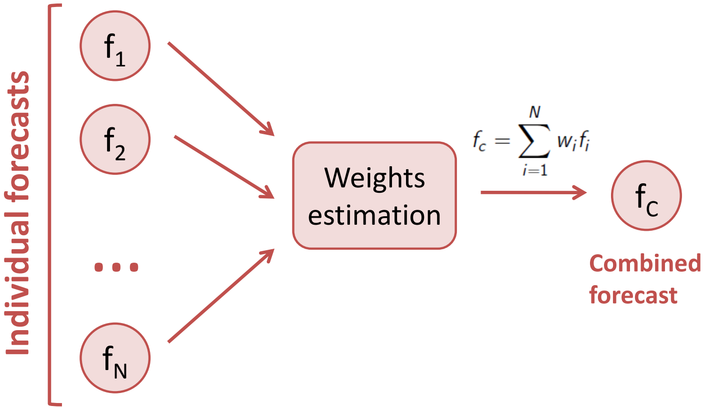
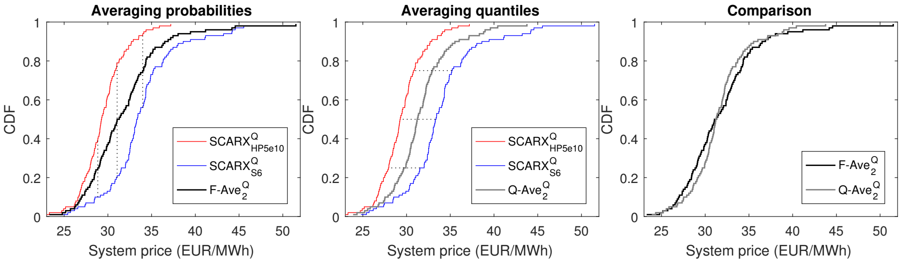
Point forecast averaging: The idea



- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger
- 'AI world': *committee machines*, *ensemble averaging*, *expert aggregation*

Combining probabilistic forecasts is more tricky

- Gneiting & Ranjan (2013): a linearly combined probabilistic forecast is more dispersed than the least dispersed of the component distributions
  - Helps if the component distributions tend to be underdispersed
- Lichtendahl et al. (2013): averaging quantiles is better (sharper)



Alternative: Quantile Regression Averaging (QRA)

(Submitted on 31.12.2013, 21:26 ;-)

Comput Stat (2015) 30:791–803
DOI 10.1007/s00180-014-0523-0

CrossMark

ORIGINAL PAPER

OPEN ACCESS

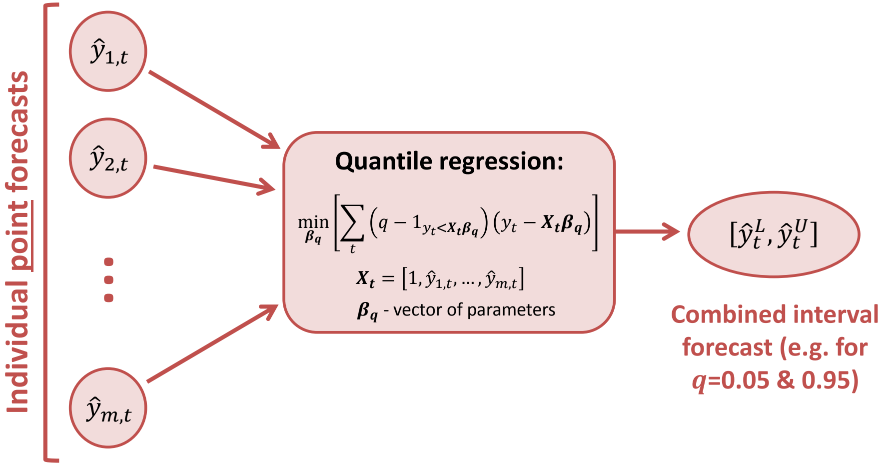
Computing electricity spot price prediction intervals using quantile regression and forecast averaging

Jakub Nowotarski · Rafał Weron

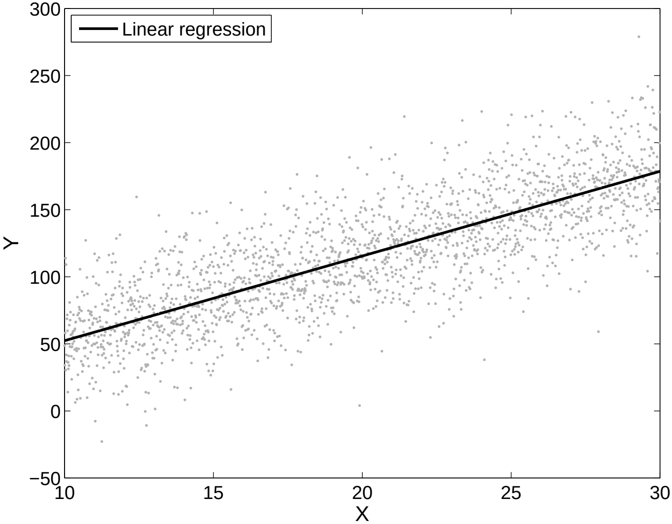
Received: 31 December 2013 / Accepted: 6 August 2014 / Published online: 19 August 2014

Abstract We examine possible accuracy gains from forecast averaging in the context of interval forecasts of electricity spot prices. First, we test whether constructing empirical prediction intervals (PI) from combined electricity spot price forecasts leads to better forecasts than those obtained from individual methods. Next, we propose a new method for constructing PI—Quantile Regression Averaging (QRA)—which utilizes the concept of quantile regression and a pool of point forecasts of individual

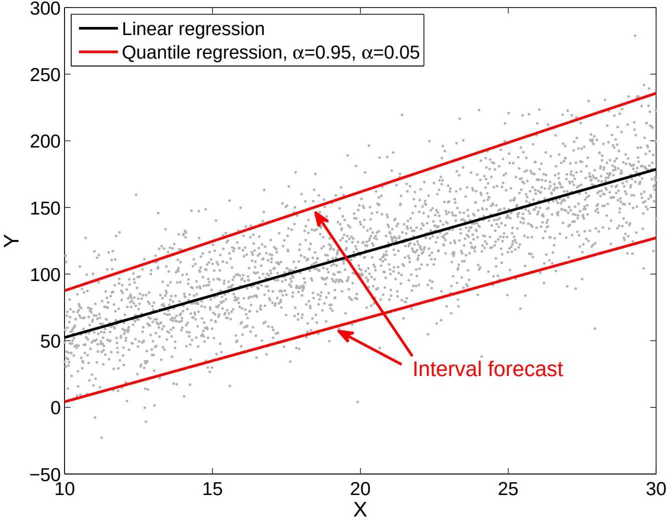
Quantile Regression Averaging: The idea



Quantile regression



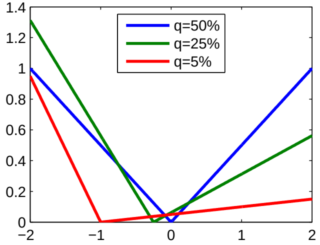
Quantile regression



How does the score function look like?

For vector $\boldsymbol{X_t} = [1, \hat{y}_{1,t}, \ldots, \hat{y}_{m,t}]$ of point forecasts, i.e. explanatory variables, weights $\boldsymbol{\beta_q}$ are estimated by minimizing:

$$\min_{\boldsymbol{\beta_q}} \left[\sum_{\{t: y_t \geqslant \boldsymbol{X_t}\beta_{\boldsymbol{q}}\}} q|y_t - \boldsymbol{X_t}\boldsymbol{\beta_q}| + \sum_{\{t: y_t < \boldsymbol{X_t}\beta_{\boldsymbol{q}}\}} (1-q)|y_t - \boldsymbol{X_t}\boldsymbol{\beta_q}| \right]$$



Case study

978-1-4799-6095-8/14/$31.00 ©2014 IEEE

Merging quantile regression with forecast averaging to obtain more accurate interval forecasts of Nord Pool spot prices

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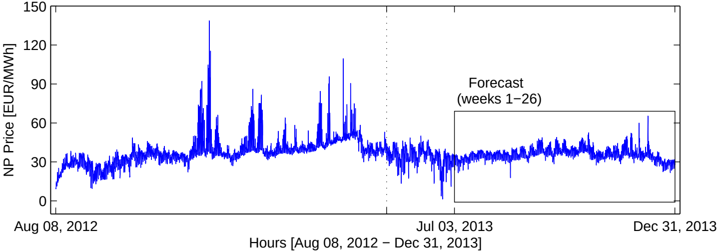
***Abstract*—We evaluate a recently proposed method for constructing prediction intervals, which utilizes the concept of quantile regression (QR) and a pool of point forecasts of different time series models. We find that in terms of interval forecasting of Nord Pool day-ahead prices the new QR-based approach significantly outperforms prediction intervals obtained from standard, as well as, semi-parametric autoregressive time series models.**

tions we are interested in PI, i.e. intervals which contain the true values of future observations with specified probability, not in confidence intervals.

From a practical point of view, PI provide additional information on price forecasts. High volatility and uncertainty of electricity price forecasts may frequently deviate from the true price levels. In fact, possible errors in point predictions

QRA at work



- Nord Pool hourly prices (2012-2013)
  - **Seven** months for calibration of individual models
  - **Four** weeks for calibration of quantile regression
  - **26** weeks for evaluation of interval forecasts
- **Six** individual point forecasting models
  - AR, TAR, SNAR, MRJD, NAR, FM

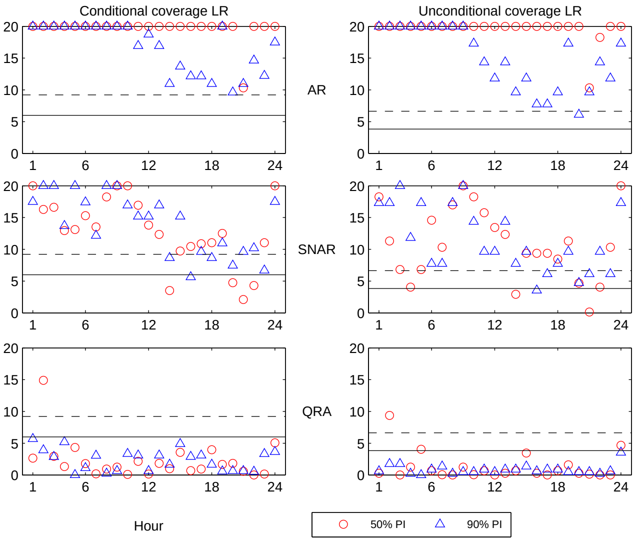
Evaluation of forecasts

- 50% and 90% two-sided day-ahead prediction intervals
- Two benchmark models: AR and SNAR
- Christoffersen's (1998, IER) test for unconditional and conditional coverage
- The focus on the sequence: $I_t = \begin{cases} 1 & y_t \in [\hat{y}_t^L, \hat{y}_t^U] \\ 0 & y_t \notin [\hat{y}_t^L, \hat{y}_t^U] \end{cases}$
- Conditional Coverage test (UC + independece) Asymptotically $\chi^2(2)$ — Unconditional Coverage test Asymptotically $\chi^2(1)$

Results: Unconditional coverage

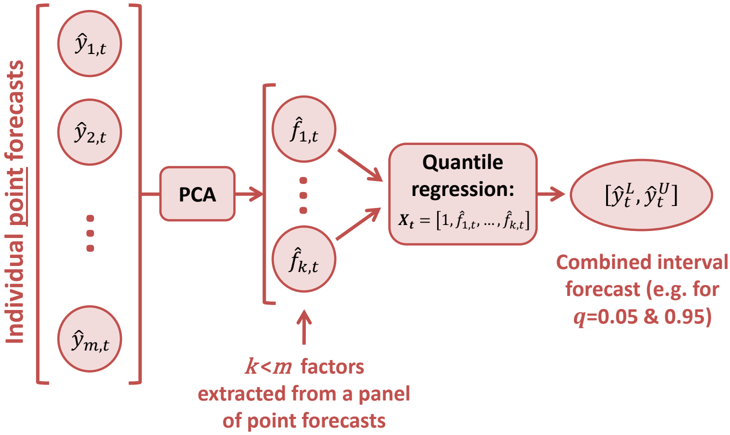
PI	AR	SNAR	**QRA**
	Unconditional coverage		
50%	77.50	61.93	**49.77**
90%	97.53	96.41	**89.33**
	Mean width (STD of interval width)		
50%	4.55 (1.34)	2.76 (0.61)	**2.23 (0.81)**
90%	11.14 (3.31)	9.33 (2.45)	**6.78 (2.20)**

Results: Christoffersen's test



FQRA: When the number of predictors is large

(Maciejowska, Nowotarski & Weron, 2016, IJF)



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Automated variable selection

Consider a general regression:

$$\hat{y}_i = \sum_{j=1}^{p} \beta_j x_{i,j} + \varepsilon_i$$

How to select predictors $x_{i,j}$? How to estimate β_j's?

- Single-step elimination of insignificant predictors
  - In EPF: Gianfreda & Grossi (2012)
- Stepwise regression
  - Forward stepwise selection
  - Backward stepwise elimination
  - In EPF: Karakatsani & Bunn (2008), Misiorek (2008), Bessec et al. (2016), Keles et al. (2016)

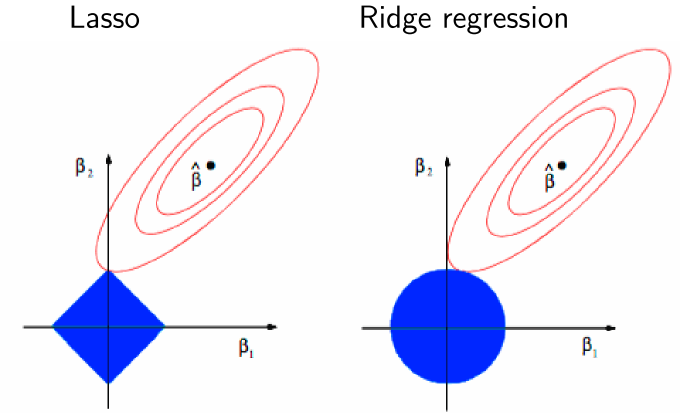
What is shrinkage (regularization)?

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

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

- Ridge regression ($q = 2$)
  - Introduced by: Hoerl & Kennard (1970, Technometrics)
  - In EPF: Barnes & Balda (2013)
- Least Absolute Shrinkage & Selection Operator (LASSO; $q = 1$)
  - Introduced by: Tibshirani (1996, JRSSB)
  - In EPF: Ludwig et al. (2015), Ziel et al. (2015), Gaillard et al. (2016), Ziel (2016), Ziel and Weron (2016)

How does it work?

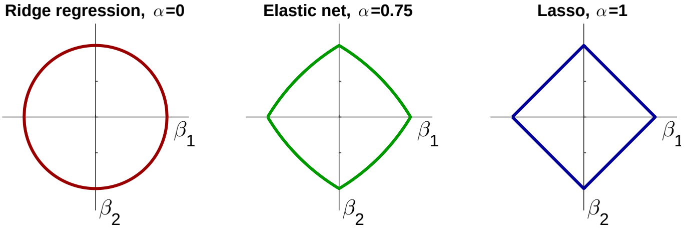


Blue areas – constraint regions, i.e., $|\beta_1| + |\beta_2| \leqslant t$ and $\beta_1^2 + \beta_2^2 \leqslant t$
Red ellipses – contours of the least squares error function

Elastic net

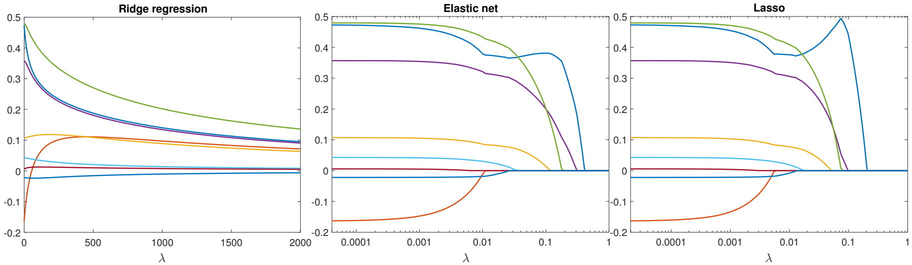
- RSS penalized by a mixed quadratic and linear shrinkage factor

$$\hat{\beta}^{EN} = \underset{\beta_j}{\operatorname{argmin}} \left\{ \mathrm{RSS} + \lambda \left(\frac{1-\alpha}{2} \sum_{j=1}^{n} \beta_j^2 + \alpha \sum_{j=1}^{n} |\beta_j| \right) \right\}$$



- Introduced by: Zou & Hastie (2015, JRSSB)
- In EPF: Uniejewski, Nowotarski & Weron (2016, Energies)

How $\hat{\beta}$'s change when λ increases?



- *Left*: Ridge regression with $\lambda \in (0, 2000)$, linear scale
- *Center*: Elastic net with $\alpha = 0.5$ and $\lambda \in (0, 1)$, log-scale
- *Right*: Lasso with $\lambda \in (0, 1)$, log-scale

Results: WMAE errors

(Uniejewski et al., 2016, Energies)

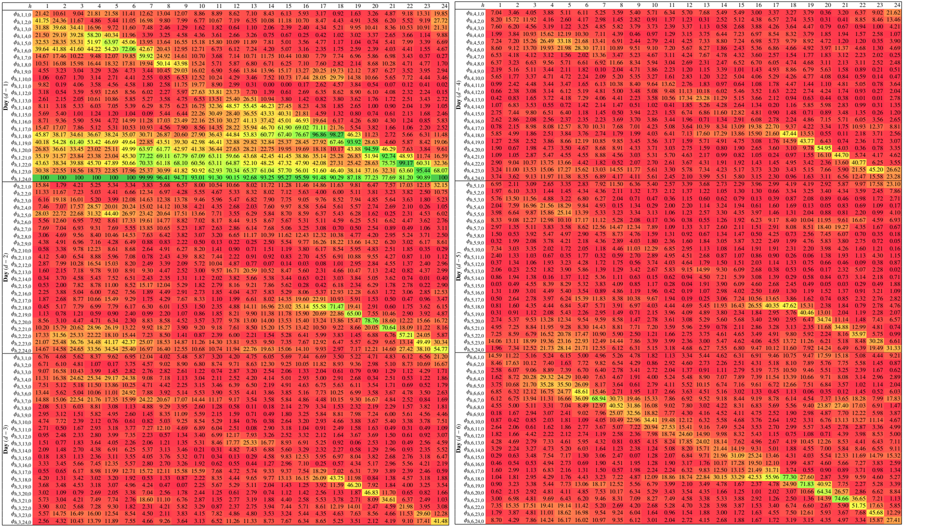
Full ARX model, 107 variables:

- 72 hourly prices from 3 previous days
- min, max & average price of 3 previous days
- 2 load forecasts, one lagged (1, 7 days)
- weekly seasonality (daily dummies, multiplied by loads or by prices)

	ARX-type			AR-type		AR - ARX
	GEFCom	Nord Pool		GEFCom	N2EX (UK)	GEFCom
Naive	14.708 (0.975)	11.141 (0.778)	**Naive**	14.708 (0.975)	9.767 (0.310)	0.000
Expert benchmarks						
ARX1	11.069 (0.639)	9.739 (0.614)	**AR1**	11.183 (0.701)	8.384 (0.253)	0.114
ARX1h	11.072 (0.639)	9.693 (0.616)	**AR1h**	11.181 (0.704)	8.389 (0.253)	0.109
ARX1hm	10.976 (0.617)	8.673 (0.516)	**AR1hm**	11.062 (0.657)	8.229 (0.247)	0.086
mARX1	11.102 (0.621)	9.482 (0.601)	**mAR1**	11.320 (0.696)	8.258 (0.253)	0.218
mARX1h	11.105 (0.622)	9.461 (0.602)	**mAR1h**	11.322 (0.699)	8.270 (0.254)	0.218
mARX1hm	10.974 (0.598)	8.461 (0.518)	**mAR1hm**	11.168 (0.644)	**8.098** (0.246)	0.195
ARX2	10.742 (0.575)	8.878 (0.546)	**AR2**	11.331 (0.700)	8.290 (0.253)	0.589
ARX2h	10.739 (0.575)	8.826 (0.546)	**AR2h**	11.333 (0.704)	8.288 (0.253)	0.594
ARX2hm	10.625 (0.565)	8.206 (0.485)	**AR2hm**	11.070 (0.656)	8.237 (0.249)	0.444
Full ARX model						
fARX	10.911 (0.507)	10.131 (0.708)	**fAR**	12.279 (0.602)	9.724 (0.334)	1.368
Selection and shrinkage methods						
ssARX	10.669 (0.577)	8.861 (0.537)	**ssAR**	12.061 (0.644)	9.344 (0.270)	1.393
ssARX1	9.894 (0.548)	8.409 (0.507)	**ssAR1**	11.343 (0.641)	8.395 (0.261)	1.449
fsARX	9.876 (0.502)	8.130 (0.502)	**fsAR**	11.193 (0.592)	8.563 (0.272)	1.317
bsARX	10.449 (0.502)	9.421 (0.599)	**bsAR**	11.968 (0.582)	9.252 (0.301)	1.519
RidgeX	9.777 (0.544)	8.972 (0.479)	**Ridge**	10.775 (0.653)	8.237 (0.260)	0.998
LassoX	9.476 (0.516)	8.419 (0.503)	**Lasso**	10.722 (0.609)	8.125 (0.253)	1.246
EN75X	9.475 (0.517)	**8.056** (0.489)	**EN75**	10.708 (0.610)	8.124 (0.253)	1.233
EN50X	**9.473** (0.518)	8.287 (0.496)	**EN50**	10.688 (0.611)	8.121 (0.253)	1.215
EN25X	9.474 (0.522)	8.529 (0.503)	**EN25**	**10.650** (0.613)	8.113 (0.253)	1.176

Variable significance across hours

(Ziel & Weron, 2016, RePEc)



Variable significance across hours cont.

(Ziel & Weron, 2016, RePEc)

	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 $(d-7)$	$\phi_{h,7,1,0}$	7.63	5.08	3.28	11.69	8.09	8.32	18.94	20.24	12.53	6.10	5.94	8.06	6.96	7.17	12.78	10.98	11.13	7.86	5.03	11.65	13.40	6.63	10.35	10.54
	$\phi_{h,7,2,0}$	16.14	11.99	4.62	3.70	2.92	3.55	5.05	4.44	11.14	7.41	6.32	5.74	3.29	2.73	3.46	2.97	4.23	2.38	1.77	2.54	1.32	1.49	4.26	2.13
	$\phi_{h,7,3,0}$	1.65	10.53	14.62	6.82	4.46	3.43	4.02	1.83	2.20	3.16	0.97	0.41	0.17	1.26	1.88	3.93	3.42	6.11	6.35	2.36	1.01	0.73	5.93	7.78
	$\phi_{h,7,4,0}$	7.89	14.45	28.85	32.46	18.52	4.86	10.64	5.65	6.67	6.48	7.67	9.94	17.36	13.55	16.59	12.07	11.26	11.73	12.06	8.80	6.65	2.24	0.98	1.79
	$\phi_{h,7,5,0}$	5.21	5.88	11.13	17.71	28.45	9.01	6.09	1.43	1.56	4.23	8.84	11.41	11.21	12.19	10.50	7.18	5.89	6.53	5.90	2.28	6.20	3.85	1.63	0.83
	$\phi_{h,7,6,0}$	5.00	2.84	7.63	6.19	15.50	43.53	12.10	4.73	11.38	10.83	7.28	6.44	5.37	4.96	2.35	3.12	2.86	2.23	4.12	6.06	5.88	2.55	1.37	8.15
	$\phi_{h,7,7,0}$	5.99	4.39	2.83	4.79	9.45	37.85	74.12	34.04	18.63	11.32	5.94	5.88	8.05	7.11	8.02	7.40	7.43	10.37	16.85	21.78	28.56	32.35	12.63	21.31
	$\phi_{h,7,8,0}$	3.20	5.40	6.25	6.09	9.49	16.02	41.35	63.65	47.78	27.13	14.78	8.92	5.73	7.79	7.44	7.63	8.76	6.76	17.32	17.44	20.32	17.89	11.19	16.41
	$\phi_{h,7,9,0}$	6.76	7.22	9.06	7.16	7.29	5.64	6.15	18.23	48.89	45.78	23.62	16.16	9.05	6.86	5.43	4.41	5.85	3.72	11.26	5.79	4.48	6.48	12.23	10.53
	$\phi_{h,7,10,0}$	8.02	7.89	8.82	10.34	7.53	4.73	2.92	8.38	19.97	40.90	26.43	16.12	13.11	8.84	3.83	3.81	3.67	2.81	2.40	6.92	7.19	5.73	3.92	3.51
	$\phi_{h,7,11,0}$	3.70	5.69	4.66	2.22	2.50	3.87	0.26	0.22	3.90	11.45	23.37	14.97	5.28	4.83	2.64	1.93	0.30	0.92	3.55	4.95	6.20	5.69	2.54	4.18
	$\phi_{h,7,12,0}$	0.35	1.04	2.75	4.93	6.16	3.89	0.33	0.80	4.52	11.54	23.58	25.99	14.21	10.18	7.84	4.39	4.77	3.79	5.97	8.33	9.88	10.76	9.23	5.54
	$\phi_{h,7,13,0}$	8.67	14.66	10.44	6.65	1.95	4.12	2.00	1.31	1.45	3.44	13.25	20.35	23.09	17.65	9.94	3.94	4.42	10.78	14.03	14.69	18.83	13.79	16.34	7.68
	$\phi_{h,7,14,0}$	0.98	3.28	4.48	3.80	4.68	3.14	0.46	3.28	5.48	16.18	24.23	31.74	40.15	39.80	33.42	25.45	11.10	10.58	11.57	11.17	9.28	9.85	10.78	11.24
	$\phi_{h,7,15,0}$	2.51	2.48	1.88	3.55	4.23	3.67	2.36	5.51	5.07	8.20	8.46	19.33	29.07	33.27	31.92	20.39	11.72	11.09	2.91	2.50	1.75	4.80	10.69	9.05
	$\phi_{h,7,16,0}$	1.71	1.37	2.61	1.23	1.56	1.18	2.96	8.90	6.31	7.56	7.45	9.05	18.90	30.08	40.75	43.55	26.06	13.35	15.82	11.09	7.72	8.80	12.07	9.67
	$\phi_{h,7,17,0}$	1.15	0.10	1.22	3.24	0.78	1.68	1.66	5.41	3.00	11.73	19.36	23.54	23.14	32.93	43.37	50.99	74.85	44.31	14.12	8.74	5.34	7.43	8.15	12.32
	$\phi_{h,7,18,0}$	5.17	4.04	3.54	3.47	5.08	5.51	1.80	5.13	5.29	9.02	14.89	16.87	31.49	36.37	31.46	25.29	33.01	64.05	38.59	4.06	3.80	1.07	3.03	3.31
	$\phi_{h,7,19,0}$	2.28	8.38	7.88	8.89	11.79	11.65	13.45	19.51	14.12	10.86	14.54	12.97	9.90	13.94	8.90	14.39	13.80	31.28	64.06	39.26	8.67	8.23	8.92	10.24
	$\phi_{h,7,20,0}$	6.90	3.15	8.81	13.58	17.73	17.47	14.03	4.51	6.36	7.14	4.36	4.77	5.70	5.99	4.44	5.98	6.36	1.02	4.20	64.78	35.84	13.33	7.72	0.41
	$\phi_{h,7,21,0}$	1.94	5.95	11.41	15.17	15.01	19.16	16.86	9.81	9.61	4.19	1.90	3.44	3.92	5.08	6.38	6.69	12.72	6.25	1.92	2.44	21.43	10.86	4.80	4.89
	$\phi_{h,7,22,0}$	1.92	9.97	12.42	13.71	9.17	10.11	8.71	4.24	6.52	5.05	3.55	0.83	1.59	3.79	9.39	8.51	9.19	14.18	15.43	4.14	0.58	20.74	9.44	2.53
	$\phi_{h,7,23,0}$	3.06	14.16	25.30	28.82	30.17	36.45	28.01	20.00	10.29	10.65	5.89	2.38	3.73	8.66	17.44	22.40	27.80	38.14	33.85	23.71	10.64	2.35	11.74	5.47
	$\phi_{h,7,24,0}$	1.48	4.50	4.36	10.01	13.63	18.41	17.36	15.93	12.52	8.19	6.52	7.43	10.97	12.09	18.52	18.73	22.12	22.65	23.41	22.86	10.06	2.78	3.32	14.86
Day $(d-8)$	$\phi_{h,8,1,0}$	5.88	6.91	15.66	20.37	22.41	20.24	17.72	18.14	15.94	11.14	4.26	5.04	5.84	7.88	7.94	10.02	11.18	10.41	14.16	12.92	10.13	7.03	4.33	3.76
	$\phi_{h,8,2,0}$	17.69	3.78	5.43	2.55	2.91	4.06	5.59	4.12	4.61	1.64	3.43	5.17	3.76	3.67	4.53	3.10	6.29	3.89	2.39	2.70	8.73	6.11	5.93	4.30
	$\phi_{h,8,3,0}$	4.15	4.83	6.61	6.46	6.49	6.69	4.27	5.57	3.95	1.49	3.93	3.87	3.02	5.50	4.56	6.86	5.40	4.91	5.71	4.19	4.89	7.03	5.49	4.02
	$\phi_{h,8,4,0}$	11.20	8.46	7.18	11.54	15.78	17.29	6.24	4.83	8.18	3.87	5.82	2.19	4.28	5.65	7.90	11.29	15.53	14.31	12.58	16.80	14.51	10.53	2.80	10.74
	$\phi_{h,8,5,0}$	0.27	2.15	4.47	9.21	9.26	5.91	5.03	7.37	6.97	5.64	5.57	8.18	11.15	9.40	7.90	6.55	8.36	4.05	2.59	3.64	2.17	0.45	1.25	1.94
	$\phi_{h,8,6,0}$	10.72	7.53	8.52	12.95	12.53	17.23	5.86	1.19	2.07	0.63	2.47	4.03	3.34	4.59	2.97	2.88	2.73	3.43	4.77	4.01	1.97	0.54	0.39	1.05
	$\phi_{h,8,7,0}$	8.81	7.72	10.22	9.29	6.51	5.46	9.04	2.10	2.04	3.52	5.26	5.87	13.78	17.31	16.14	13.55	11.60	7.62	5.67	7.67	5.84	3.44	3.21	0.65
	$\phi_{h,8,8,0}$	4.66	3.17	4.08	6.15	6.49	3.50	2.51	4.39	2.98	1.84	1.42	2.29	2.39	1.83	2.56	3.74	4.18	3.26	4.79	5.99	7.79	5.16	2.82	2.47
	$\phi_{h,8,9,0}$	3.13	1.67	3.79	3.18	3.40	4.29	4.10	0.76	0.43	0.81	0.59	0.43	0.55	0.87	2.50	2.12	13.36	7.87	6.47	3.09	4.44	4.18	3.86	0.62
	$\phi_{h,8,10,0}$	5.83	2.25	0.88	1.13	2.08	6.66	6.47	1.08	0.29	1.60	2.49	4.73	5.84	7.38	6.11	6.97	10.43	12.64	11.80	9.22	4.73	1.13	1.56	2.26
	$\phi_{h,8,11,0}$	8.79	3.54	5.52	1.91	6.17	3.53	6.37	3.69	2.83	1.62	1.41	0.46	0.09	0.09	0.43	1.43	1.11	1.84	3.16	2.85	1.77	0.93	3.06	0.35
	$\phi_{h,8,12,0}$	3.27	3.30	5.23	4.42	5.16	8.83	4.32	2.98	1.76	2.16	1.53	1.83	0.54	0.09	0.29	0.46	0.63	2.31	4.66	1.62	1.34	0.46	0.15	1.10
	$\phi_{h,8,13,0}$	0.36	0.19	1.05	1.50	2.84	3.01	6.30	2.61	2.82	1.32	3.46	4.78	2.72	1.62	2.72	2.98	2.98	2.29	0.66	0.07	0.39	0.16	0.00	1.77
	$\phi_{h,8,14,0}$	0.46	3.25	4.82	5.10	4.88	8.39	3.63	4.69	3.54	1.21	1.37	2.59	5.73	3.88	2.55	1.60	0.50	1.63	0.54	0.51	2.19	1.20	1.58	1.50
	$\phi_{h,8,15,0}$	2.19	0.73	0.43	3.11	6.34	0.54	3.39	5.84	6.03	1.99	0.66	1.17	1.79	2.17	2.68	2.88	5.60	5.23	1.91	0.15	0.21	0.18	0.82	1.15
	$\phi_{h,8,16,0}$	1.44	0.17	0.51	0.39	1.39	0.99	0.47	0.81	1.09	1.86	2.07	6.94	9.02	8.58	8.83	9.69	2.49	0.68	0.53	0.35	0.22	0.81	2.34	2.54
	$\phi_{h,8,17,0}$	2.40	0.85	0.89	2.46	5.15	6.12	6.21	1.46	3.99	1.03	0.12	3.53	2.27	5.12	3.19	8.51	17.71	12.80	4.82	6.57	6.28	9.64	8.58	8.68
	$\phi_{h,8,18,0}$	2.52	1.07	0.80	0.94	4.46	3.60	6.07	2.51	6.72	4.24	3.01	1.92	3.06	4.27	4.58	6.70	12.62	33.95	14.70	1.75	1.91	9.46	6.98	2.66
	$\phi_{h,8,19,0}$	7.50	3.67	3.57	7.86	9.93	6.87	2.20	6.61	12.92	7.01	2.59	3.42	3.50	5.13	5.20	2.38	0.79	3.05	23.49	11.22	0.78	7.32	5.08	1.11
	$\phi_{h,8,20,0}$	4.16	2.46	8.50	11.45	13.97	12.30	9.71	15.00	6.37	5.97	6.68	5.25	5.85	4.23	4.84	5.81	4.88	3.70	3.47	20.80	7.43	2.55	5.23	1.74
	$\phi_{h,8,21,0}$	7.25	12.75	16.64	17.77	16.35	7.40	3.42	15.39	7.08	8.85	6.45	9.65	6.87	5.48	12.20	9.48	10.70	9.66	6.38	5.55	14.34	1.82	4.11	5.72
	$\phi_{h,8,22,0}$	4.33	8.93	10.04	16.30	12.54	7.28	4.64	4.91	3.29	0.34	1.96	1.72	1.56	1.07	2.47	1.92	3.46	6.31	6.93	1.18	8.10	26.47	8.96	4.88
	$\phi_{h,8,23,0}$	4.56	15.33	26.87	30.59	31.56	20.93	21.06	9.42	6.06	3.55	2.21	3.01	5.48	5.35	5.33	5.20	7.48	11.30	12.26	9.60	3.58	5.07	23.33	7.84
	$\phi_{h,8,24,0}$	7.34	7.58	11.25	12.36	13.77	17.66	13.78	13.75	11.42	10.62	10.16	6.56	7.43	8.48	10.14	10.85	8.36	9.18	5.80	4.67	3.00	3.83	9.83	11.31

	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
Daily minimums	$\phi_{h,1,\min,0}$	57.99	66.16	80.84	87.56	81.33	54.23	26.01	25.68	20.48	12.72	6.94	5.83	5.42	4.45	7.03	5.54	7.51	5.76	3.28	1.68	5.52	2.91	3.02	7.03
	$\phi_{h,2,\min,0}$	1.01	8.69	13.20	16.20	14.91	12.35	7.52	5.59	3.04	0.15	0.80	1.04	0.95	2.96	3.39	2.68	2.46	1.30	3.75	2.50	1.61	2.15	1.31	3.23
	$\phi_{h,3,\min,0}$	14.29	22.78	22.77	27.55	24.29	18.38	7.56	4.16	4.36	1.51	1.15	1.67	2.45	1.71	1.26	0.97	2.66	1.23	1.70	2.63	5.09	4.54	2.83	3.50
	$\phi_{h,4,\min,0}$	7.84	8.01	11.65	18.02	16.59	12.95	10.40	6.07	1.03	1.34	1.55	2.70	4.06	3.14	5.44	4.67	9.50	15.95	13.49	7.01	6.25	2.85	2.45	3.22
	$\phi_{h,5,\min,0}$	11.53	11.88	21.48	24.25	24.12	13.21	4.08	3.53	0.79	1.89	3.01	4.72	5.50	4.94	4.06	6.11	7.26	3.43	4.33	1.60	2.67	3.86	2.25	1.44
	$\phi_{h,6,\min,0}$	5.37	13.53	23.47	21.92	27.64	25.79	5.19	1.04	3.11	2.32	1.92	2.08	4.27	2.84	2.87	6.69	5.96	3.65	1.56	1.22	1.75	0.50	1.60	2.70
	$\phi_{h,7,\min,0}$	6.48	8.76	13.14	13.48	13.01	5.66	1.90	2.00	0.86	0.26	0.60	1.44	3.69	1.77	1.67	3.56	3.01	3.91	4.35	5.00	5.07	4.00	3.01	1.14
	$\phi_{h,8,\min,0}$	2.46	2.39	6.19	8.26	13.44	7.23	6.97	8.70	6.67	8.64	9.21	10.91	13.49	14.41	13.37	13.08	8.00	7.85	5.49	4.43	3.72	3.80	5.30	6.04
Daily maximums	$\phi_{h,1,\max,0}$	24.53	13.83	21.30	26.21	27.31	21.85	21.41	55.76	62.53	47.56	31.51	25.43	14.92	9.67	6.72	4.31	7.13	7.79	10.33	15.28	7.53	4.03	3.48	3.90
	$\phi_{h,2,\max,0}$	18.14	22.28	25.77	22.57	24.48	16.80	29.67	28.34	24.89	19.93	17.27	14.70	13.86	12.42	6.20	5.94	7.78	2.30	2.96	5.66	8.43	12.15	10.50	7.15
	$\phi_{h,3,\max,0}$	4.96	2.13	7.05	6.47	9.85	10.09	17.09	17.45	15.70	18.45	12.69	8.36	5.49	4.18	0.85	2.04	1.72	0.57	3.99	8.18	15.13	5.33	6.29	4.23
	$\phi_{h,4,\max,0}$	8.31	6.60	5.04	6.54	9.67	6.31	11.52	12.08	10.09	7.87	12.16	8.80	5.78	4.59	4.28	1.30	1.23	1.66	1.87	1.64	3.80	3.60	5.17	11.70
	$\phi_{h,5,\max,0}$	4.73	0.99	4.84	6.88	6.73	3.34	12.91	12.73	11.82	10.93	15.06	15.22	13.08	12.24	11.68	11.31	7.51	8.38	9.51	9.74	4.63	1.08	0.49	0.87
	$\phi_{h,6,\max,0}$	4.04	4.79	4.34	2.91	1.65	1.12	9.46	30.53	30.04	22.47	6.36	2.66	2.35	4.07	4.14	4.70	5.36	6.53	7.78	11.33	9.90	5.09	5.95	2.27
	$\phi_{h,7,\max,0}$	5.20	6.41	13.87	12.78	7.82	14.09	11.58	12.96	15.77	9.49	8.63	8.26	7.30	8.10	7.71	8.68	3.50	3.59	2.66	1.86	2.93	0.89	1.13	3.55
	$\phi_{h,8,\max,0}$	3.87	3.78	2.41	2.89	4.93	5.86	4.38	2.19	2.95	4.50	2.98	2.97	2.02	1.81	2.10	2.56	2.91	2.43	6.39	7.43	6.87	7.05	9.85	9.80
DoW dummies	$\phi_{h,0,0,1}$	22.61	22.29	27.32	25.24	22.66	60.04	88.09	85.89	93.59	97.73	95.53	94.01	95.86	97.22	99.46	99.71	99.94	99.97	99.73	96.70	93.83	87.32	73.40	53.01
	$\phi_{h,0,0,2}$	27.80	46.46	42.87	42.67	45.42	40.12	36.81	43.44	37.81	34.31	30.82	38.15	31.30	37.60	46.98	51.57	52.96	53.39	40.40	28.78	32.96	40.62	33.46	24.70
	$\phi_{h,0,0,3}$	20.98	13.92	15.17	16.09	8.92	14.69	14.61	14.43	14.14	16.02	13.59	15.13	9.03	15.42	19.23	16.85	13.52	17.48	18.64	17.04	19.64	14.92	7.36	3.24
	$\phi_{h,0,0,4}$	23.87	14.91	21.66	21.47	18.69	18.97	20.21	19.36	13.52	14.35	10.08	10.34	14.68	12.45	12.84	14.37	16.01	15.17	23.05	17.48	12.33	7.32	13.14	7.89
	$\phi_{h,0,0,5}$	9.69	12.23	10.71	9.38	10.49	6.86	7.96	5.14	9.29	6.80	7.45	6.65	5.25	6.49	21.41	35.71	26.50	13.57	24.00	38.13	32.87	45.01	29.89	7.29
	$\phi_{h,0,0,6}$	74.08	60.13	55.84	50.60	30.44	92.69	93.32	97.92	99.54	98.71	98.26	93.64	95.58	99.32	99.88	99.84	99.45	97.65	95.34	94.63	97.24	90.99	74.01	64.73
	$\phi_{h,0,0,7}$	52.63	76.93	78.50	78.29	87.97	90.70	89.07	100	100	100	100	100	100	100	100	100	100	98.57	90.35	82.90	73.49	66.47	34.57	50.06
Periodic on $Y_{*,h}$	$\phi_{h,1,h,1}$	18.71	12.25	13.46	14.93	20.98	19.94	20.08	26.92	16.09	22.81	25.79	24.16	22.43	22.62	21.48	23.51	34.66	33.15	34.28	41.74	43.25	34.87	20.82	17.60
	$\phi_{h,1,h,2}$	21.02	16.13	20.15	15.90	13.89	15.38	32.89	33.32	31.00	27.40	31.94	25.89	19.21	24.91	33.36	37.56	44.95	43.46	39.35	32.49	33.03	27.80	30.85	9.19
	$\phi_{h,1,h,3}$	13.65	15.59	26.42	25.76	27.98	31.84	68.69	70.35	72.61	51.85	45.71	48.85	51.43	60.35	67.56	72.94	65.23	58.87	55.16	48.27	33.88	31.34	25.93	15.86
	$\phi_{h,1,h,4}$	35.22	29.29	28.70	35.39	32.62	34.95	63.99	58.20	40.96	31.24	30.25	36.67	42.75	50.46	64.26	66.44	56.31	42.92	38.92	45.47	50.13	49.53	32.71	27.66
	$\phi_{h,1,h,5}$	14.19	28.57	37.94	46.53	36.81	33.22	69.44	76.08	58.60	50.74	47.77	33.40	29.93	19.74	12.16	18.72	26.38	21.65	49.85	32.55	29.84	22.96	15.27	15.82
	$\phi_{h,1,h,6}$	14.39	20.29	19.67	21.81	24.78	44.99	33.90	59.18	48.95	41.35	33.06	33.66	34.78	33.12	31.68	27.99	28.23	13.78	16.30	31.64	19.69	18.37	7.03	27.03
	$\phi_{h,1,h,7}$	29.57	28.45	26.33	28.86	34.16	40.50	24.74	14.12	17.23	13.60	19.40	39.36	41.85	51.45	55.81	54.55	47.65	45.33	36.21	22.29	32.53	33.50	20.88	45.95
Periodic on $Y_{*,24}$	$\phi_{h,1,24,1}$	26.28	24.95	33.33	45.40	41.39	40.10	35.49	25.15	35.69	28.84	26.79	24.19	23.58	14.07	13.97	16.84	18.89	24.81	28.17	26.45	20.64	17.31	14.14	
	$\phi_{h,1,24,2}$	19.80	32.47	45.61	46.47	53.83	57.98	44.03	41.65	33.04	30.98	28.06	27.04	29.38	28.67	30.53	30.74	31.22	32.76	28.73	27.22	19.48	18.88	5.30	
	$\phi_{h,1,24,3}$	18.96	32.24	34.27	42.07	36.84	40.72	31.93	45.29	34.20	29.24	23.01	23.69	22.46	17.62	16.92	15.80	19.28	22.54	18.85	13.86	19.55	11.35	15.59	
	$\phi_{h,1,24,4}$	12.84	27.89	35.46	31.46	40.28	46.01	41.86	44.74	49.17	36.89	27.92	25.85	24.19	18.63	21.74	25.02	30.40	31.96	33.81	27.32	16.69	11.51	12.94	
	$\phi_{h,1,24,5}$	9.65	13.64	19.73	29.84	30.10	23.46	27.57	27.44	30.70	23.16	16.36	16.51	15.68	21.26	29.18	27.49	25.98	25.70	18.82	18.04	23.68	20.49	19.56	
	$\phi_{h,1,24,6}$	35.57	37.69	52.08	52.65	37.73	31.88	41.40	51.12	55.28	49.51	49.57	51.32	51.22	43.32	39.75	32.02	33.27	41.09	40.48	42.39	44.14	35.53	30.17	
	$\phi_{h,1,24,7}$	45.76	40.57	40.44	41.43	35.29	25.55	30.70	35.73	42.99	44.31	43.30	43.39	43.64	24.10	20.25	21.58	28.77	39.88	41.91	46.51	38.83	30.33	33.96	

Agenda

1. Beyond point forecasts
   ⇒ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Variable selection and shrinkage
   - LASSO
   - Elastic nets
4. **Guidelines for evaluating forecasts**

International Journal of Forecasting 30 (2014) 1030–1081

Contents lists available at ScienceDirect

International Journal of Forecasting

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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

1 2 4

energies

Energies **2016**, *9*, 621; doi:10.3390/en9080621

MDPI

Article

Automated Variable Selection and Shrinkage for Day-Ahead Electricity Price Forecasting

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Renewable and Sustainable Energy Reviews xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

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

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

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ARTICLE INFO

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

ABSTRACT

Since the inception of competitive power markets two decades ago, *electricity price forecasting* (EPF) has gradually become a fundamental process for energy companies' decision making mechanisms. Over the years, the bulk of research has concerned point predictions. However, the recent introduction of smart grids and renewable integration requirements has had the effect of increasing the uncertainty of future supply, demand and prices. Academics and practitioners alike have come to understand that probabilistic electricity price (and load) forecasting is now more important for energy systems planning and operations than ever before. With this paper we offer a tutorial review of probabilistic EPF and present much needed guidelines for the rigorous use of methods, measures and tests, in line with the paradigm of 'maximizing sharpness subject to reliability'. The paper can be treated as an update and a further extension of the otherwise comprehensive EPF review of Weron [1] or as a standalone treatment of a fascinating and underdeveloped topic, that has a much broader reach than EPF itself.

Guidelines for evaluating probabilistic forecasts

Renewable and Sustainable Energy Reviews xxx (2017) xxx–xxx

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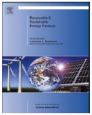

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Maximizing *sharpness* subject to *reliability*

(Gneiting & Katzfuss, 2014; Nowotarski & Weron, 2017)

- *Reliability* refers to statistical consistency (x% PI covers x% of obs.)
- *Sharpness* refers to how tightly the PI covers the observations

Interval forecasts **Statistics**	**Tests**	**Density forecasts** **Statistics**	**Tests**
Reliability / calibration / unbiasedness			
Unconditional coverage [46, 74]	Kupiec [74]	Probability Integral Transform (PIT) [14, 75]	Visual 'tests' [14, 16] *Tests for uniformity* [76, 77]
Conditional coverage [46] (CC = UC + Independence)	Christoffersen [46] (*Lagged* [78]) *Ljung-Box Christoffersen* [79] *Duration-based tests* [80, 81] *Dynamic Quantile (DQ)* [82] *VQR* [83]	Berkowitz CC statistic [48]	Berkowitz [48]
Sharpness (and reliability)			
Pinball loss [84, 85] Winkler (interval) score [86]	Diebold-Mariano [87, 88] *Model confidence set* [89] *Forecast encompassing* [90]	Continuous Ranked Probability Score (CRPS) [15, 91] *Logarithmic score* [92]	Diebold-Mariano [87, 88] *Model confidence set* [89] *Forecast encompassing* [90]

Take-home messages

1. Beyond point forecasts
   $\Rightarrow$ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Variable selection and shrinkage
   - LASSO
   - Elastic nets
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...rice forecasting (EPF) over ... article aims to explain the ...ses, and the opportunities ... countered. The paper also ...d take in the next decade ...tive EPF studies involving ...edures, and (iii) statistical ...other.

energies

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