Forecasting wholesale electricity prices to support decision-making in power companies: Use of regularization and forecast combinations

Bartosz Uniejewski

Supervisor: prof. dr hab. Rafał Weron
Auxiliary supervisor: dr Katarzyna Maciejowska

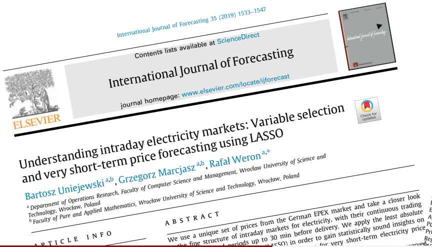
Department of Operations Research and Business Inteligence
Faculty of Management

Aims and objectives

Aim: Develop robust and efficient electricity price forecasting (EPF) techniques to support decision-making in power companies

Objectives:

1. Use regularization to identify the most relevant predictors **[P1]**
2. Develop a fully-automated approach to average a rich pool of individual forecasts using regularization and PCA **[P2]**


International Journal of Forecasting 35 (2019) 1533–1547

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Understanding intraday electricity markets: Variable selection and very short-term price forecasting using LASSO

Bartosz Uniejewski a,b, Grzegorz Marcjasz a,b, Rafał Weron a,*

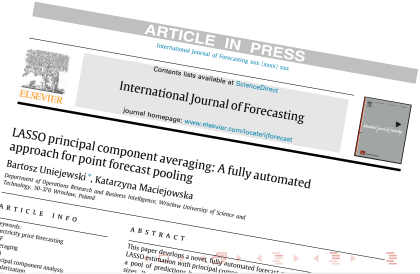
a Department of Operations Research, Faculty of Computer Science and Management, Wrocław University of Science and Technology, Wrocław, Poland

b Faculty of Pure and Applied Mathematics, Wrocław University of Science and Technology, Wrocław, Poland

ARTICLE INFO

ABSTRACT

We use a unique set of prices from the German EPEX market and take a closer look at the fine structure of intraday markets for electricity, with their continuous trading ... periods up to 30 min before delivery. We apply the least absolute ... (LASSO) in order to gain statistically sound insights on ... for very short-term electricity price ...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LASSO principal component averaging: A fully automated approach for point forecast pooling

Bartosz Uniejewski *, Katarzyna Maciejowska

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

ARTICLE INFO

Keywords:
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EPF
Averaging
PCA
Principal component analysis
Regularization

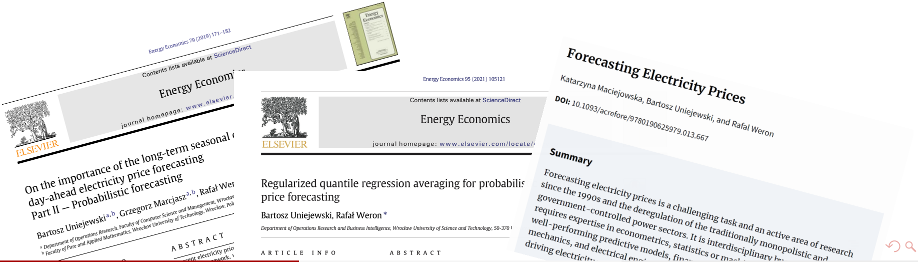
ABSTRACT

This paper develops a novel, fully automated forecast ... LASSO estimation with principal comp... a pool of predictions ...

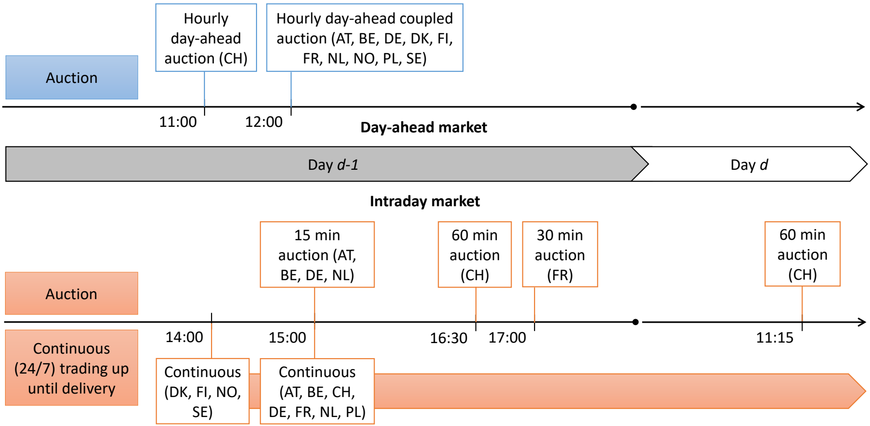
Aims and objectives

Objectives:

3. Utilize quantile regression and regularization to construct more accurate algorithms for probabilistic EPF **[P3-P4]**
4. Design a trading strategy to evaluate the economic value of probabilistic forecasts **[P4]**
5. Conduct a critical review of EPF and provide an outlook for future research in this area **[P5]**

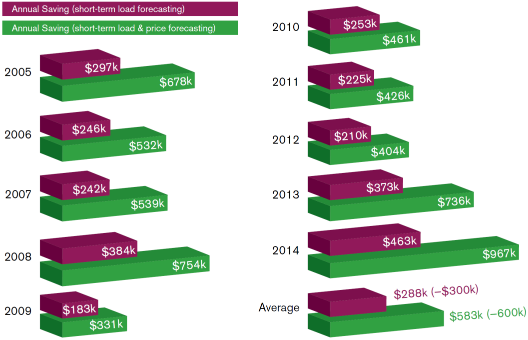


Day-ahead and intraday power markets



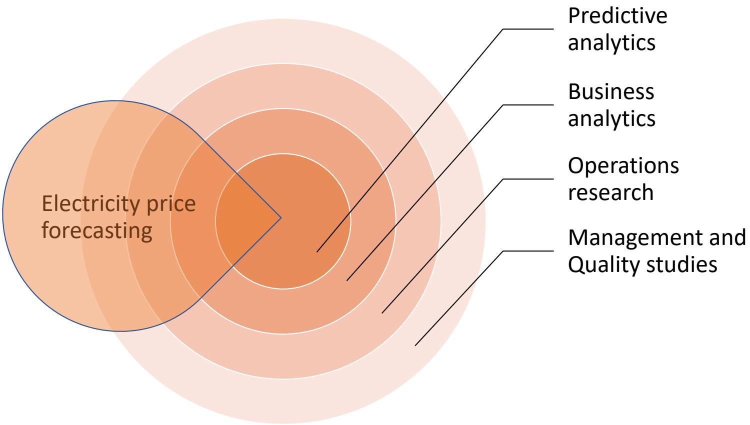
Importance of electricity price forecasting (EPF)

- Price and load forecasting errors reduced by 1% → savings of ca. $600,000 per year (for 1 GW peak load)
- PGE (17.8 GW), ENEA (6.2), TAURON (6.1), Energa (1.4)



Source: Hong (2015, EnergyBiz)

EPF in Management and Quality Studies



[P1] Variable selection (Intraday market)

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Understanding intraday electricity markets: Variable selection and very short-term price forecasting using LASSO

Bartosz Uniejewski [a,b], Grzegorz Marcjasz [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

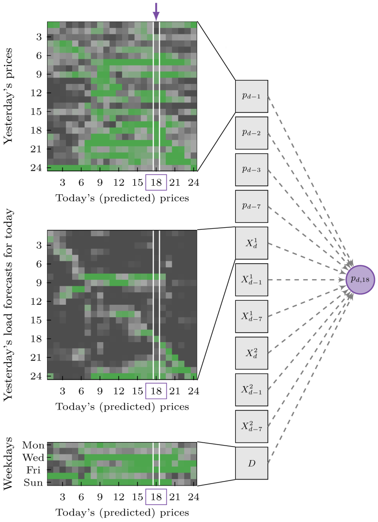
Keywords:
Intraday electricity market
Variable selection
Price forecasting
LASSO
ARX model
Diebold-Mariano test
Trading strategy

ABSTRACT

We use a unique set of prices from the German EPEX market and take a closer look at the fine structure of intraday markets for electricity, with their continuous trading for individual load periods up to 30 min before delivery. We apply the *least absolute shrinkage and selection operator* (LASSO) in order to gain statistically sound insights on variable selection and provide recommendations for very short-term electricity price forecasting.

Obj. 1: Variable selection

LASSO



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

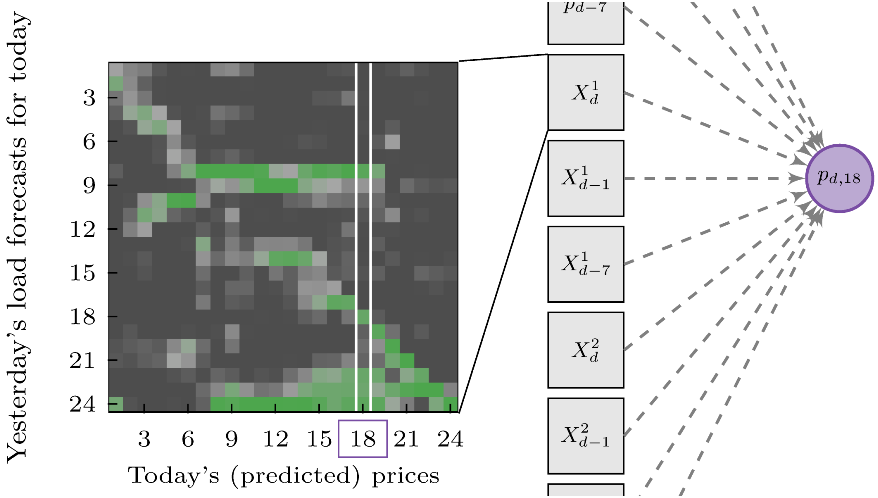
$$\hat{\beta} = \underset{\beta_j}{\operatorname{argmin}} \left\{ \text{RSS} + \lambda \sum_{j=1}^{n} |\beta_j| \right\}$$

- Allows designing sparse models
- Easy to interpret
- Fast estimation

Source: Jędrzejewski et al. (2022, IEEE PEM)

Obj. 1: Variable selection

LASSO



[P1] Contribution and conclusions

- Major step forward towards understanding the intraday price dynamics
- LASSO significantly outperforms benchmarks
- LASSO helps to identify the most important variables

	Naive	ARX	LASSO									
			λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	λ_{10}
MAE	5.0323	4.7234	5.2198	4.9454	4.7323	4.5728	4.4672	4.4135	4.4128	4.4680	4.5704	4.6928
RMSE	8.1098	7.6513	8.0331	7.6670	7.4196	7.2370	7.1122	7.0721	7.1095	7.2356	7.4416	7.6834

[P2] Automated forecast combination

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LASSO principal component averaging: A fully automated approach for point forecast pooling

Bartosz Uniejewski *, Katarzyna Maciejowska

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A R T I C L E   I N F O

Keywords:
Electricity price forecasting
EPF
Averaging
PCA
Principal component analysis
Regularization
LASSO
Day-ahead market
Risk management

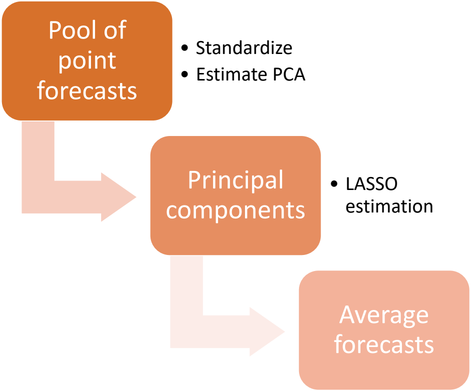
A B S T R A C T

This paper develops a novel, fully automated forecast averaging scheme which combines LASSO estimation with principal component averaging (PCA). LASSO-PCA (LPCA) explores a pool of predictions based on a single model but calibrated to windows of different sizes. It uses information criteria to select tuning parameters and hence reduces the impact of researchers' ad hoc decisions. The method is applied to average predictions of hourly day-ahead electricity prices over 650 point forecasts obtained with various lengths of calibration windows. It is evaluated on four European and American markets with an out-of-sample period of almost two and a half years and compared to other semi- and fully automated methods, such as the simple mean, AW/WAW, LASSO, and PCA. The results indicate that LASSO averaging is very efficient in terms of forecast error reduction, whereas PCA is robust to the selection of the specification parameter. LPCA inherits the advantages of both methods and outperforms other approaches in terms of the mean absolute error, remaining insensitive to the choice of a tuning parameter.

Obj. 2: Automated forecast combination

LASSO PCA

- Improves forecast accuracy
- Reduces the risk
- Can cope with highly correlated forecasts
- Limited studies on using regularization



[P2] Contribution and conclusions

- Averaging significantly improves forecast accuracy
- LASSO PCA (LPCA) model outperforms competitors
- BIC helps to select optimal model parameters

	EPEX		NP		OMIE		PJM		
	MAE	% chng	MAE	% chng	MAE	% chng	MAE	% chng	m.p.d.b.
728	5.88	-	2.24	-	3.26	-	3.31	-	-
best	5.14	-12.53	2.16	-3.65	3.10	-5.04	3.30	-0.28	-5.37
simple average	5.27	-10.22	2.07	-7.71	3.02	-7.45	3.27	-1.15	-6.63
LASSO(BIC)	5.00	-14.81	1.99	-11.23	2.90	-11.21	3.26	-1.48	-9.68
PCA(BIC)	5.02	-14.59	1.99	-11.34	2.95	-9.54	3.25	-1.69	-9.29
LPCA(BIC)	4.92	-16.21	1.98	-11.69	2.92	-10.43	3.22	-2.76	-10.27

m.d.f.b. - mean deviation from the benchmark

[P3-P4] Probabilistic forecasting with LASSO & QR

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ELSEVIER

On the importance of the long-term seasonal component in day-ahead electricity price forecasting
Part II — Probabilistic forecasting

Bartosz Uniejewski[a,b], Grzegorz Marcjasz[a,b], Rafał Weron[a,*]

[a] Department of Operations Research, Faculty of Computer Science and Management, Wrocław University of Technology, Wroc
[b] Faculty of Pure and Applied Mathematics, Wrocław University of Technology, Wrocław, Poland

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Keywords:
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Seasonal Component AutoRegressive (SCAR) model
Probabilistic forecasting
Risk management
Quantile Regression Averaging (QRA)
Pinball score

ABSTRACT

A recent electricity price forecasting study has shown tl modeling framework, which consists of decomposing a stochastic component, modeling them independently ar accurate point predictions than an approach in which tl prices themselves. Here, we show that further accuracy ables (load forecasts) are deseasonalized as well. More i SCAR concept to probabilistic forecasting and applying tv we find that (i) SCAR-type models nearly always significa are in turn outperformed by combined SCAR forecasts, (ii Regression Averaging (QRA) outperform those obtained f and (iii) averaging over predictive distributions generall spot prices than averaging over quantiles. Given that prol risk management, our study has important implications fo sector.

Energy Economics 95 (2021) 105121

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Regularized quantile regression averaging for probabilistic electricity price forecasting

Check for updates

Bartosz Uniejewski, Rafał Weron *

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

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Electricity price forecasting
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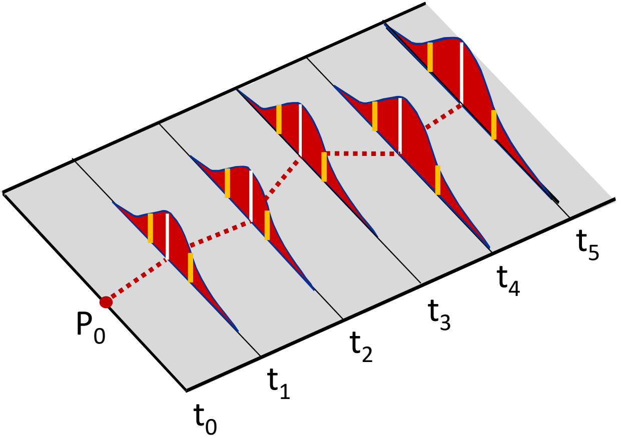
Quantile Regression Averaging (QRA)
LASSO
Bayesian Information Criterion (BIC)
Cross-validation
Kupiec test

ABSTRACT

Quantile Regression Averaging (QRA) has sparked interest in the electricity price forecasting community after its unprecedented success in the Global Energy Forecasting Competition 2014, where the top two winning teams in the price track used variants of QRA. However, recent studies have reported the method's vulnerability to low quality predictors when the set of regressors is larger than just a few. To address this issue, we consider a regularized variant of QRA, which utilizes the Least Absolute Shrinkage and Selection Operator (LASSO) to automatically select the relevant regressors. We evaluate the introduced technique – dubbed LASSO QRA or LQRA for short – using datasets from the Polish and Nordic power markets. By comparing against a number of benchmarks, we provide evidence for its superior predictive performance in terms of the Kupiec test, the pinball score and the test for conditional predictive accuracy, as well as financial profits for a range of trading strategies, especially when the regularization parameter is selected *ex-ante* using the Bayesian Information Criterion (BIC). As such, we offer an efficient tool that can be used to boost the profitability of energy trading activities, help with bidding in day-ahead markets and improve risk management practices in the power sector.

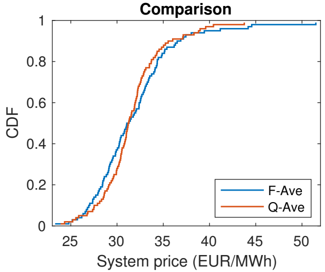
Obj. 3: Probabilistic forecasting

- Provides much more information about the future price
- Related to Value-at-Risk (VaR)
- Provides better ground for decision-making



[P3] LTSC and combining forecasts

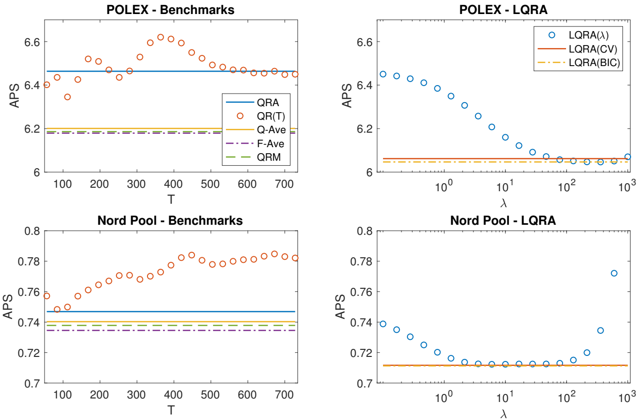
- SCAR-based models significantly outperform the benchmarks
- Forecast combination improves reliability and sharpness of probabilistic predictions



	Benchmarks & SCARX with HP filter (λ)									
	Naive	ARX	10^8	$5 \cdot 10^8$	10^9	$5 \cdot 10^9$	10^{10}	$5 \cdot 10^{10}$	10^{11}	$5 \cdot 10^{11}$
Historical (H)	3.269	2.472	2.772	2.694	2.487	2.410	2.371	2.381	2.390	2.388
Bootstrap (B)	-	2.468	2.998	2.810	2.526	2.425	2.368	2.380	2.386	2.372
QRA (Q)	3.189	2.431	2.702	2.615	2.420	2.349	2.313	2.333	2.366	2.343

[P4] LASSO QRA (LQRA)

- LQRA significantly outperforms the standard QRA
  - in terms of reliability and sharpness

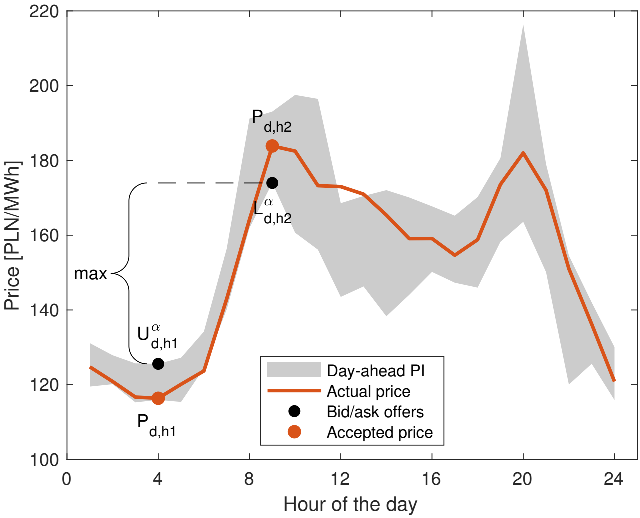


Obj. 4: Economic value of probabilistic forecasts

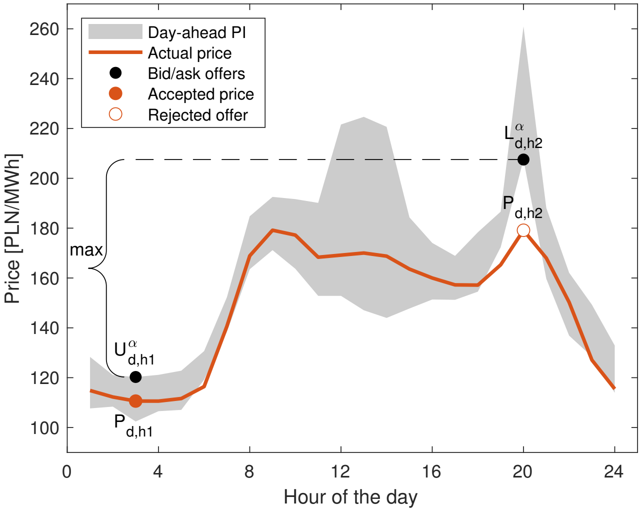
Trading strategy

- The company owns a 1.25 MWh battery
  - it cannot be discharged below 0.25 MWh
- Efficiency: 80% for a single charge-discharge cycle
- We maximize trading profits

[P4] Decision based on probabilistic forecasts



[P4] Decision based on probabilistic forecasts



[P4] Contribution and conclusions

- Probabilistic forecasts are an effective tool in decision-making
- Better forecast = better decision

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

[P5] Review and outlook

Forecasting Electricity Prices

Katarzyna Maciejowska, Bartosz Uniejewski, and Rafal Weron

DOI: 10.1093/acrefore/9780190625979.013.667

Summary

Forecasting electricity prices is a challenging task and an active area of research since the 1990s and the deregulation of the traditionally monopolistic and government-controlled power sectors. It is interdisciplinary by nature and requires expertise in econometrics, statistics or machine learning for developing well-performing predictive models, finance for understanding market mechanics, and electrical engineering for comprehension of the fundamentals driving electricity prices.

[P5] Literature trends

1. From regression to statistical & machine learning **[P1-P2, P4]**
   - increase forecast accuracy
   - automated variable selection
2. From point to probabilistic forecasts **[P3-P4]**
   - more information about the future price
   - improves the decision-making process
3. From statistical to economic evaluation **[P4]**
   - assessing real value of forecasts
   - quantifying economic benefits

Key findings

- Regularization helps to understand the intraday price dynamics
- Fully-automated averaging model improves forecast accuracy
- Forecast combination improves prediction accuracy for probabilistic EPF
- Probabilistic forecasts are an effective tool in decision-making
- Three trends are visible in the recent EPF literature

Papers

1. **Uniejewski, B.**, Marcjasz, G., Weron, R., 2019. Understanding intraday electricity markets: Variable selection and very short-term price forecasting using LASSO. International Journal of Forecasting [IF_{5Y}=7.022, 140p MEiN]
2. **Uniejewski, B.**, Maciejowska, K., 2023. LASSO principal component averaging – a fully automated approach for point forecast pooling. International Journal of Forecasting [IF_{5Y}=7.022, 140p MEiN]
3. **Uniejewski, B.**, Marcjasz, G., Weron, R., 2019. On the importance of the long-term seasonal component in day-ahead electricity price forecasting: Part II – Probabilistic forecasting. Energy Economics [IF_{5Y}=9.252, 200p MEiN]
4. **Uniejewski, B.**, Weron, R., 2021. Regularized quantile regression averaging for probabilistic electricity price forecasting. Energy Economics [IF_{5Y}=9.252, 200p MEiN]
5. Maciejowska, K., **Uniejewski, B.**, Weron, R., 2023. Forecasting electricity prices. Oxford Research Encyclopedia of Economics and Finance [75p MEiN]

- 8 more JCR-listed publications on energy forecasting
- Scopus: 332 citations (excluding self-citations of all authors) and H-index = 11

Replies to reviews

1. Choice of transformation

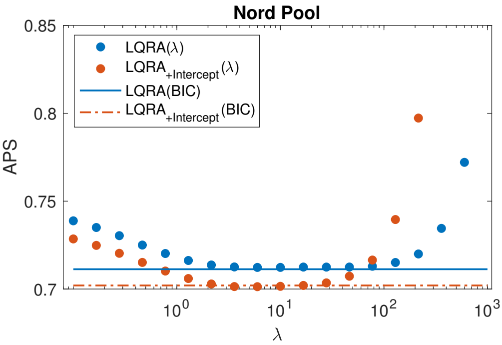
- The choice of the optimal transformation depends on the forecasting framework and the considered dataset

VST	BELPEX.BE	EPEX.DE+AT	EXAA.DE+AT	NP.SYS	OMIE.ES	OTE.CZ	GEFCom2014
original	6.385	5.447	4.374	1.830	6.042	4.698	8.144
3σ [1]	6.203	5.305	4.334	1.817	6.383	4.689	9.320
3σlog [1]	6.250	5.347	4.350	1.803	6.073	4.710	7.974
logistic [1]	6.205	5.382	4.372	1.830	6.346	4.735	8.346
asinh [1]	6.192	5.331	4.310	1.775	6.092	4.672	7.563
boxcox [1]	6.256	5.382	4.320	1.785	6.007	4.697	7.628
poly [1]	6.261	5.355	4.314	1.785	6.019	4.690	7.665
mlog [1]	6.227	5.368	4.332	1.784	6.037	4.693	7.701
N-ecdf	6.219	5.308	4.332	1.789	5.989	4.680	7.401
t-ecdf	6.292	5.355	4.395	1.834	5.952	4.721	7.384

Reference(s): **Uniejewski, B.**, Weron, R., Ziel, F., 2018. *Variance stabilizing transformations for electricity spot price forecasting.* IEEE Transactions on Power Systems

2. Penalizing all parameters in LASSO

- All parameters were penalized **[P1-P2, P4]**
- Variables were centered **[P1-P2]**
- An empirical study has been conducted to address this issue:



3. LASSO vs. other regularization techniques

- Easy to implement
- Fast to estimate
- 'Only' one additional parameter

Reference(s): **Uniejewski B.**, 2023. *Regularization in forecasting electricity prices.* Working paper

	EPEX-DE		OMIE	
	ARX	full	ARX	full
OLS	**7.67**	7.05	**5.24**	5.20
Adaptive	8.14	6.71	**5.28**	4.88
Clipped	7.86	6.66	5.38	4.81
Concave	7.87	6.57	5.29	4.76
Elastic	**7.84**	6.57	**5.27**	**4.74**
FLASH	**7.83**	6.59	5.36	4.79
LASSO	7.86	6.56	5.28	4.76
LQ	**7.82**	6.57	**5.26**	**4.74**
MC	**7.85**	6.68	5.42	4.82
Ridge	**7.74**	6.63	**5.26**	4.77
SCAD	**7.84**	6.71	5.41	4.85

1. Human expertise vs. automated forecasting

- More data and computational power – expert knowledge no longer enough to handle them (Jędrzejewski et al., 2022)
- Automated models yield more accurate forecasts
- But ... all models use expert knowledge to some extent
- Expert judgment improves forecast accuracy (Maciejowska and Nowotarski, 2016)
- Expert knowledge used by practitioners

Reference(s): Maciejowska, K., Nowotarski, J., 2016. *A hybrid model for GEFCom2014 probabilistic electricity price forecasting.* International Journal of Forecasting; Jędrzejewski, A., Lago, J., Marcjasz, G., Weron, R., 2022. *Electricity price forecasting: The dawn of machine learning.* IEEE Power & Energy Magazine

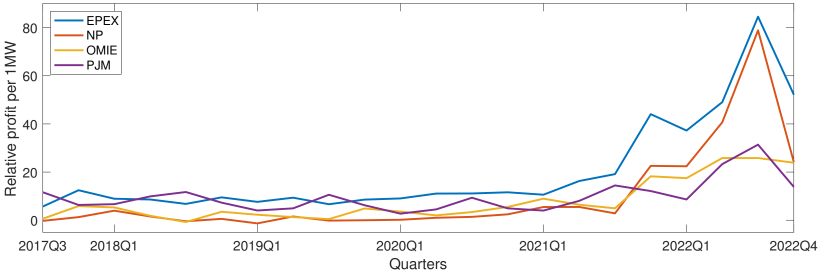
2. Meteorological data in EPF

- Limited studies on using meteorological data in EPF
- RES generation is derived from weather forecasts
- Forecasts featuring meteorological data are 10–20% more accurate (Sgarato and Ziel, 2023)

Reference(s): Sgarlato, R., and Ziel, F., 2022. *The role of weather predictions in electricity price forecasting beyond the day-ahead horizon*. IEEE Transactions on Power Systems

3. Battery cost vs. profitability

- Battery cost: ∼1250 PLN per kW or ∼1.25M PLN for 1MW
- Profit: ∼20K PLN per year
- Break even: ∼62 years
- However ...



3. Battery cost vs. profitability

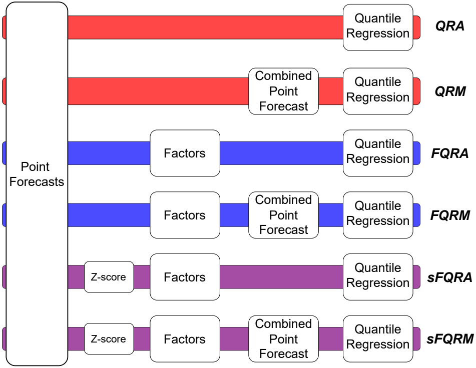
- Battery cost: $\sim$300$ per kW or $\sim$1.25M PLN for 1MW
- Profit: $\sim$360 PLN per day ($\sim$130K PLN/year)
- Break even: $<$10 years

Reference(s): **Uniejewski B.**, 2023. *Smoothing Quantile Regression Averaging: A new approach to probabilistic forecasting of electricity prices*. arXiv

1. LPCA and probabilistic forecasting

- Factors improve forecast reliability

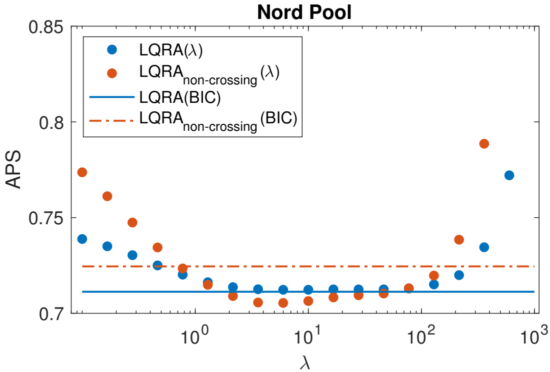
Kupiec test	80%	90%	98%
QRA	0	0	0
QRM	0	1	0
FQRA	0	1	4
FQRM	0	0	4
sFQRA	9	14	20
sFQRM	10	12	17



Reference(s): Maciejowska K., Serafin T., **Uniejewski B.**, 2023. *Probabilistic forecasting with Factor Quantile Regression: Application to electricity trading*. arXiv

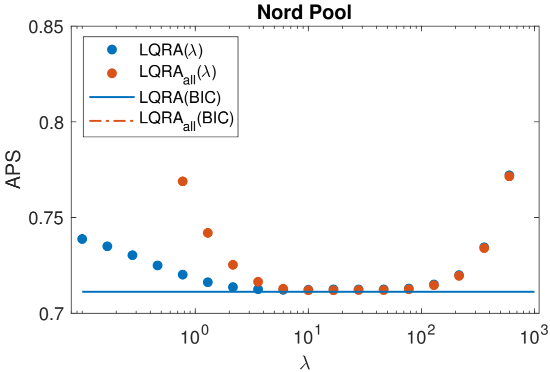
Quantile crossing problem

- Quantiles are sorted **[P3-P4]**
- Fast and efficient
- An empirical study has been conducted to address this issue:



Number of inputs in LQRA

- Problem of collinearity
- Time consuming
- An empirical study has been conducted to address this issue:



Thank you!

LASSO QRA (LQRA)

$$q(\alpha|X_{d,h}) = \boldsymbol{\beta}_\alpha X_{d,h}$$

The estimator of $\boldsymbol{\beta}_\alpha$ is:

$$\hat{\boldsymbol{\beta}} = \text{argmin}\left\{\underbrace{\sum_{d,h}(\alpha - \mathbb{1})(P_{d,h} - \sum_{i=1}^{n}\beta_\alpha^i \hat{P}_{d,h}^i)}_{\text{pinball score}} + \underbrace{\lambda\sum_{i=1}^{n}|\beta_\alpha^i|}_{\text{LASSO penalty}}\right\}.$$

- where $\hat{P}_{d,h}^i$ – point forecast of price $P_{d,h}^i$ obtained for model i

LASSO: estimation vs. variable selection

MAE	Id	asinh	mlog	poly	NPIT	m.p.d.f.b
naive			2.3338			66.6194
ARX1	1.9254	1.8491	1.8467	1.8482	1.8143	32.4139
ARX2	1.7506	1.6422	1.6263	1.6272	1.6363	18.0834
ARX3	1.6713	1.4831	1.4773	1.4805	1.491	8.2652
bARX1	1.802	1.5447	1.5413	1.5518	1.5519	13.7047
bARX2	2.527	2.1671	2.14	2.1362	2.0143	56.1632
24xNLassOLS_2	1.6641	1.3799	1.3800	1.3936	1.3640	2.0797
2xNLassOLS_2	1.7021	1.3801	1.3821	1.3954	1.3656	2.6477
1xNLassOLS_2	1.6778	1.3749	1.3818	1.3942	1.3604	2.1620
24LassOLS_2	1.6802	1.3829	1.3906	1.4056	1.3852	2.9725
2LassOLS_2	1.6759	1.3713	1.3846	1.4084	1.3715	2.4944
1LassOLS_2	1.6818	1.3725	1.3794	1.4084	1.3715	2.5119
24xNLasso_2	1.5766	1.3483	1.3800	1.3936	1.3454	0.2203
2xNLasso_2	1.5849	1.3401	1.3821	1.3954	1.3404	0.1882
1xNLasso_2	1.5917	1.3391	1.3818	1.3942	1.3427	0.2696
24Lasso_2	1.5996	1.3459	1.3906	1.4056	1.3587	1.0023
2Lasso_2	1.6031	1.3419	1.3846	1.4084	1.3565	0.9067
1Lasso_2	1.5999	1.3419	1.3794	1.4084	1.3565	0.7917

Reference(s): **Uniejewski, B.**, Weron, R., 2018. *Efficient forecasting of electricity spot prices with expert and LASSO models.* Energies

Bayesian Model Averaging

	DA		IDA		ID		m.p.d.f.b
Benchmarks	**MAE**	**%chng**	**MAE**	**%chng**	**MAE**	**%chng**	**%chng**
56	5.412	7.348 %	9.270	22.232 %	6.464	29.953 %	19.845 %
364	5.312	5.380 %	7.641	0.753 %	5.047	1.455 %	2.529 %
728	5.560	10.297 %	7.770	2.444 %	4.974	0.000 %	4.247 %
Best	5.041 (95)	–	7.584 (438)	–	4.974 (728)	–	–
Averaging							
AW(56:728)	5.062	0.422 %	7.437	-1.945 %	5.011	0.746 %	-0.259 %
WAW(56:728)	5.053	0.239 %	7.440	-1.901 %	5.009	0.688 %	-0.325 %
BMA(56:728)	5.126	1.685 %	7.540	-0.580%	4.999	0.498%	0.534%
AW(56.84.112.714.721.728)	4.875	-3.299 %	7.464	-1.590 %	5.135	3.232 %	-0.552 %
WAW(56.84.112.714.721.728)	4.865	-3.484 %	7.450	-1.775 %	5.100	2.529 %	-0.910 %
BMA(56.84.112.714.721.728)	5.224	3.633 %	7.789	2.698%	4.977	0.063%	2.131%
PCA(1)	4.888	-3.030 %	7.425	-2.097 %	5.004	0.597 %	-1.510 %
PCA(2)	4.864	-3.515 %	7.466	-1.560 %	5.001	0.526 %	-1.516 %
PCA(3)	4.852	-3.757 %	7.489	-1.261 %	4.996	0.436 %	-1.527 %
PCA(4)	4.847	-3.841 %	7.487	-1.286 %	5.000	0.510 %	-1.539 %
PCA(BIC)	4.858	-3.632 %	7.481	-1.367%	5,003	0.571%	-1.476 %

Reference(s): Maciejowska, K., **Uniejewski, B.**, Serafin, T., 2020. *PCA forecast averaging – predicting day-ahead and intraday electricity prices,* Energies