Probabilistic electricity price forecasting (EPF) ... and related topics

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

*Based on work with Jakub Nowotarski (PWr & BNY Mellon), Grzegorz Marcjasz (PWr) and Bartosz Uniejewski (PWr)
Markets for electricity in Europe

- N2EX (UK)
- EPEX Spot (AT, CH, DE, FR)
- OMIE (ES, PT)
- Nord Pool (DK, EST, FIN, NOR, SWE)
- APX-ENDEX (NL)
- PolPX (PL)
- OTE (CZ)
- Belpex (BE)
- EPEX Spot (AT, CH, DE, FR)
- GME (IT)
- Borzen (SLO)
- HUPX (HU)
- OKTE (SK)
- OPCOM (RO)

Rafał Weron (Wrocław, PL)
... in North America and Australia
The day-ahead market

- Day $D$
  - Bidding for day $D + 1$
- Day $D + 1$
  - Bidding for day $D + 2$
- Day $D + 2$
  - 24 hours of day $D + 1$
  - 24 hours of day $D + 2$
Electricity price time series
Seasonality, mean-reversion and price spikes
A closeup on two weeks in December 2016

(Almost) no wind imports + conventional generation

Evening peaks, expensive coal fired generators cover demand

Historical record, wind covers 34% of demand (exports)

Christmas (low demand, strong wind)

Wind
Conventional generators
Industrial generators, CHP, renewables (w/o wind)
System-wide demand (Poland)
Day-ahead price (TGE / PolPX)

Dane: TGE, PSE (GPI)
Grudzień 2016
Licencja: CC-BY 4.0
Supply and demand, renewables and negative prices

Source: Ziel & Steinert (2016)
Day-ahead point forecasting: Univariate...
... or multivariate?
Day-ahead point forecasting: Regression ...

Electricity price for day $d$ and hour $h$:

\[
Y_{d,h} = \beta_{h,1} + \beta_{h,2} Y_{d-1,h} + \beta_{h,3} Y_{d-2,h} + \beta_{h,4} Y_{d-7,h} + \beta_{h,5} Y_{d-1, \min} + \beta_{h,6} Y_{d-1, \max} + \beta_{h,7} Y_{d-1,24} + \sum_{j=1}^{7} \beta_{h,j+7D_j} + \varepsilon_{d,h},
\]

- **Autoregressive terms**
- **Non-linear effects**
- **End-of-day effect**
- **Weekday dummies**
... or neural nets?

\[ \begin{align*}
Y_{d-1,h} & \\
Y_{d-2,h} & \\
Y_{d-7,h} & \\
Y_{\min_{d-1}} & \\
Y_{\max_{d-1}} & \\
Y_{d-1,24} & \\
D_1 & \\
D_7 & \\
\end{align*} \]
### Variable (feature) selection using LASSO

*(Ziel & Weron, 2016, RePEc)*

---

**Table 5: Mean occurrence (in %) of the multivariate lasso model parameters across all 12 datasets and the full out-of-sample data.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Across All Datasets</th>
<th>Full Out-of-Sample Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter 1</td>
<td>3.59%</td>
<td>8.16%</td>
</tr>
<tr>
<td>Parameter 2</td>
<td>63.11%</td>
<td>10.37%</td>
</tr>
<tr>
<td>Parameter 3</td>
<td>4.19%</td>
<td>60.56%</td>
</tr>
<tr>
<td>Parameter 4</td>
<td>3.46%</td>
<td>7.43%</td>
</tr>
<tr>
<td>Parameter 5</td>
<td>38.24%</td>
<td>2.60%</td>
</tr>
<tr>
<td>Parameter 6</td>
<td>0.12%</td>
<td>3.46%</td>
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<td>Parameter 7</td>
<td>33.81%</td>
<td>23.73%</td>
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<td>15.49%</td>
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<td>Parameter 10</td>
<td>4.81%</td>
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<tr>
<td>Parameter 11</td>
<td>11.28%</td>
<td>27.90%</td>
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<tr>
<td>Parameter 12</td>
<td>1.65%</td>
<td>3.75%</td>
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<tr>
<td>Parameter 13</td>
<td>3.70%</td>
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<td>1.23%</td>
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<tr>
<td>Parameter 15</td>
<td>3.20%</td>
<td>2.08%</td>
</tr>
<tr>
<td>Parameter 16</td>
<td>9.87%</td>
<td>0.91%</td>
</tr>
<tr>
<td>Parameter 17</td>
<td>0.91%</td>
<td>3.71%</td>
</tr>
<tr>
<td>Parameter 18</td>
<td>2.61%</td>
<td>43.33%</td>
</tr>
<tr>
<td>Parameter 19</td>
<td>11.26%</td>
<td>1.17%</td>
</tr>
<tr>
<td>Parameter 20</td>
<td>2.87%</td>
<td>0.83%</td>
</tr>
</tbody>
</table>
Variable (feature) selection using LASSO cont. (Ziel & Weron, 2016, RePEc)

### Table 7: Mean occurrence (in %) of the multivariate lasso model parameters across all 12 datasets and the full out-of-sample lasso model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean Occurrence (%)</th>
</tr>
</thead>
<tbody>
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<tr>
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<tr>
<td>Lambda (λ)</td>
<td>6.97</td>
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<td>Sigma (σ)</td>
<td>3.69</td>
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<td>Alpha (α)</td>
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<td>Beta (β)</td>
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<td>Delta (δ)</td>
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</table>
First read on electricity price forecasting (EPF)

R.Hyndman: “this paper alone is responsible for 0.7 of the current IF$_2$Y = 2.642” ;-

**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

**Abstract**

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

1. Beyond point forecasts ⇒ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Seasonal components & short-term forecasting
   - SCAR framework
   - Case study
4. New trends in energy forecasting
A new hype: Point → probabilistic forecasting

1. Beyond point forecasts

Probabilistic forecasting
A (very) recent review of probabilistic forecasting

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

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.
How popular is probabilistic EPF: Papers, cites

Number of Scopus-indexed articles and citations

Number of Scopus-indexed articles

Journal articles

Citations (×50)

Neural network only

Neural network & time series

Time series only

Other methods

Probabilistic EPF

2016
2015
2014
2013
2012
2011
2010
2009
2008
2007
2006
2005
2004
2003
2002
2001
2000
<2000

Number of Scopus-indexed articles and citations

Number of Scopus-indexed articles

Journal articles

Citations (×50)

Neural network only

Neural network & time series

Time series only

Other methods

Probabilistic EPF

2016
2015
2014
2013
2012
2011
2010
2009
2008
2007
2006
2005
2004
2003
2002
2001
2000
<2000
How popular is probabilistic EPF: Journals

- IEEE Transactions on Power Systems
- Energy Conversion and Management
- Energy Economics
- Int. J. Electrical Power & Energy Systems
- Electric Power Systems Research
- IET Generation Transmission & Distribution
- International Journal of Forecasting
- Energies
- Applied Energy
- Neural Computing and Applications
- IEEE Transactions on Smart Grid

Number of Scopus-indexed articles:

- Neural network only
- Neural network & time series
- Time series only
- Other methods
- Probabilistic EPF
GEFCom2014
(Hong, Pinson, Fan et al., 2016, IJF)

- Incremental data sets released on weekly basis
- Price Track:
  - 287 contestants
  - Submit 99 quantiles (=percentiles) for 24h of the next day
Price Track

Task 10

Task 11

Task 12

Task 13

Task 14

Task 15

Legend:
- Blue: Real price
- Red: Benchmark
- Black: Median
- Dashed: 25% and 75% quantiles
- Dotted: 5% and 95% quantiles
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)
Agenda

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   - SCAR framework
   - Case study
4. New trends in energy forecasting
2. Combining forecasts

Point forecasts

Point forecast averaging: The idea

\[ f_C = \sum_{i=1}^{N} w_i f_i \]

- Dates back to the 1960s and the works of Bates, Crane, Crotty & Granger
In the ‘AI world’ …

- **Committee machines, ensemble averaging, expert aggregation**

- Weron (2014): Forecast combinations and committee machines seem to **evolve independently**, with researchers from both groups not being aware of the parallel developments!
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)
Computing electricity spot price prediction intervals using quantile regression and forecast averaging

Jakub Nowotarski · Rafał Weron

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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:
Individual point forecasts
Combined interval forecast (e.g. for $q=0.05$ & $0.95$)

\[
\min_{\beta_q} \left[ \sum_t \left( q - 1_{y_t < x_t \beta_q} \right) \left( y_t - x_t \beta_q \right) \right]
\]

\[X_t = [1, \hat{y}_{1,t}, \ldots, \hat{y}_{m,t}]\]
\[\beta_q - \text{vector of parameters}\]

Combined interval forecast (e.g. for $q=0.05$ & $0.95$)
FQRA: When the number of predictors is large
(Maciejowska, Nowotarski & Weron, 2016, IJF)

![Diagram showing the process of combining forecasts using PCA and quantile regression.](image)

- Individual point forecasts: \( \hat{y}_{1,t}, \hat{y}_{2,t}, \ldots, \hat{y}_{m,t} \)
- PCA extracts \( k \) factors from the panel of point forecasts.
- Quantile regression: \( x_t = [1, \hat{f}_{1,t}, \ldots, \hat{f}_{k,t}] \)
- Combined interval forecast (e.g. for \( q=0.05 \) & \( 0.95 \))

\( \hat{y}_L^t, \hat{y}_U^t \)
Agenda

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LTSC and short-term price forecasting

Can the long-term trend-seasonal component (LTSC) impact short-term (day-ahead) electricity price forecasts?
On the importance of the long-term seasonal component in day-ahead electricity price forecasting

Jakub Nowotarski, Rafał Weron*

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

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ABSTRACT

In day-ahead electricity price forecasting (EPF) the daily and weekly seasonalties are always taken into account, but the long-term seasonal component (LTSC) is believed to add unnecessary complexity to the already parameter-rich models and is generally ignored. Conducting an extensive empirical study involving state-of-the-art time series models we show that (i) decomposing a series of electricity prices into a LTSC and a stochastic component, (ii) modeling them independently and (iii) combining their forecasts can bring – contrary to a common belief – an accuracy gain compared to an approach in which a given time series model is calibrated to the prices themselves.
Wavelet and HP-filter based LTSCs

- **Wavelet filters** (-$S_J$): $S_5, S_6, \ldots, S_{14}$, ranging from ‘daily’ smoothing ($S_5 \rightarrow 2^5$ hours) up to ‘biannual’ ($S_{14} \rightarrow 2^{14}$ hours)

- **HP-filters** (-$\text{HP}_\lambda$): with $\lambda = 10^8, 5 \cdot 10^8, 10^9, \ldots, 5 \cdot 10^{11}$
The **ARX** model

For the log-price, i.e., \( p_{d,h} = \log(P_{d,h}) \), the model is given by:

\[
p_{d,h} = \beta_{h,1}p_{d-1,h} + \beta_{h,2}p_{d-2,h} + \beta_{h,3}p_{d-7,h} + \beta_{h,4}p_{d-1,\text{min}} + \beta_{h,5}z_t + \sum_{i=1}^{3} \beta_{h,i+5}D_i + \varepsilon_{d,h}
\]

- \( p_{d-1,\text{min}} \) is yesterday’s minimum hourly price
- \( z_t \) is the logarithm of system load/consumption
- Dummy variables \( D_1, D_2 \) and \( D_3 \) refer to Monday, Saturday and Sunday, respectively
The SCAR modeling framework
(Nowotarski & Weron, 2016, ENEECO; Uniejewski, Marcjasz & Weron, 2017, WP)

The *Seasonal Component AutoRegressive* (SCAR) modeling framework consists of the following steps:

1. (a) Decompose the log-price in the calibration window into the LTSC $T_{d,h}$ and the stochastic component $q_{d,h}$
   (b) Decompose the exogenous series in the calibration window using the same type of LTSC as for prices

2. Calibrate the **ARX** model to $q_t$ and compute forecasts for the 24 hours of the next day (24 separate series)
3. Seasonal components & short-term forecasting Models

The SCAR modeling framework cont.

Add stochastic component forecasts $\hat{q}_{d+1,h}$ to persistent forecasts $\hat{T}_{d+1,h}$ of the LTSC to yield log-price forecasts $\hat{p}_{d+1,h}$.

Convert them into price forecasts of the SCARX model, i.e.,

$$\hat{P}_{d+1,h} = \exp(\hat{p}_{d+1,h})$$
Three methods of constructing PIs

1. **Historical simulation (H)**, which consists of computing sample quantiles of the empirical distribution of $\varepsilon_{d,h}$’s

2. **Bootstrapping (B)**, which first generates pseudo-prices recursively using sampled normalized residuals, then computes desired quantiles of the bootstrapped prices
   - Takes into account not only historical forecast errors but also parameter uncertainty

3. **Quantile Regression Averaging (Q)**

**Note:** All require that one-day ahead point prediction errors are available in the calibration window for probabilistic forecasts
Datasets: GEFCom 2014

Initial calibration period for point forecasts
Initial calibration period for historical & QRA forecasts
Initial calibration period for bootstrapped forecasts
Test period for point & probabilistic forecasts

Probabilistic EPF
20.11.2017, NBP Workshop
3. Seasonal components & short-term forecasting

Probabilistic forecasts

Datasets: Nord Pool

![Graph showing price and consumption trends]

- **Price [EUR/MWh]**: Initial calibration period for point forecasts
- **Consumption [GWh]**: Initial calibration period for bootstrapped forecasts

Initial calibration period for historical & QRA forecasts

⇒ Test period for point & probabilistic forecasts

Jan 1, 2013 - Dec 24, 2015

Rafał Weron (Wrocław, PL)
Combining probabilistic forecasts

- **Average probability forecast**: $F_{\text{Ave}}^n \equiv \frac{1}{n} \sum_{i=1}^{n} \hat{F}_i(x)$
  $\Rightarrow$ a vertical average of predictive distributions

- **Average quantile forecast**: $Q_{\text{Ave}}^n \equiv \hat{Q}^{-1}(x)$
  with $\hat{Q}(x) = \frac{1}{n} \sum_{i=1}^{n} \hat{Q}_i(x)$ and quantile forecast $\hat{Q}_i(x) = \hat{F}_i^{-1}(x)$
  $\Rightarrow$ a horizontal average

- $* = H, B$ or $Q$ denotes the method of constructing PIs
Sharpness and the pinball loss

\[
\text{Pinball} \left( \hat{Q}_{P_t}(q), P_t, q \right) = \begin{cases} 
(1 - q) \left( \hat{Q}_{P_t}(q) - P_t \right), & \text{for } P_t < \hat{Q}_{P_t}(q), \\
q \left( P_t - \hat{Q}_{P_t}(q) \right), & \text{for } P_t \geq \hat{Q}_{P_t}(q), 
\end{cases}
\]

- \( \hat{Q}_{P_t}(q) \) is the price forecast at the \( q \)-th quantile
- \( P_t \) is the actually observed price

To provide an aggregate score we average:
- across all hours in the test period
- across different quantiles (all 99 or extreme 20 percentiles)
How many models should we average?

GEFCom2014, Pinball across all 99 percentiles

Nord Pool, Pinball across all 99 percentiles

GEFCom2014, Pinball across 20 extreme percentiles

Nord Pool, Pinball across 20 extreme percentiles
Diebold-Mariano (DM) tests

Define the ‘multivariate’ loss differential series in the $|| \cdot ||_1$-norm as:

$$
\Delta_{X,Y,d} = ||\pi_{X,d}||_1 - ||\pi_{Y,d}||_1
$$

where

- $\pi_{X,d} = (\pi_{X,d,1}, \ldots, \pi_{X,d,24})'$ is the vector of pinball scores for model $X$ and day $d$

- $||\pi_{X,d}||_1 = \sum_{h=1}^{24} |\pi_{X,d,h}|$ is the average across the 24 hours

As in the standard DM test, we assume that the loss differential series is covariance stationary.
Diebold-Mariano (DM) tests cont.

For each model pair we compute two one-sided DM tests:

1. \( H_0 : E(\Delta X, Y, d) \leq 0 \Rightarrow X \) yields better forecasts
2. \( H_0^R : E(\Delta X, Y, d) \geq 0 \Rightarrow Y \) yields better forecasts

We present results for 14 selected models:

- Both naive benchmarks – \textbf{Naive}^H, \textbf{Naive}^Q
- All three ARX benchmarks – \textbf{ARX}^H, \textbf{ARX}^B, \textbf{ARX}^Q
- The best \textit{ex-post}
  - \textbf{SCARX}^*_H, \textbf{SCARX}^*_B and \textbf{SCARX}^*_Q models
  - \textbf{Q-Ave}^H_n, \textbf{Q-Ave}^B_n and \textbf{Q-Ave}^Q_n average quantile forecasts
  - \textbf{F-Ave}^H_n, \textbf{F-Ave}^B_n and \textbf{F-Ave}^Q_n average probability forecasts
We use a heat map to indicate the range of the $p$-values – the closer they are to zero (→ dark green) the more significant is the difference between the forecasts of a model on the X-axis (better) and the forecasts of a model on the Y-axis (worse).
**p-values of the DM test across 20 percentiles**

We use a heat map to indicate the range of the $p$-values – the closer they are to zero (→ dark green) the more significant is the difference between the forecasts of a model on the X-axis (better) and the forecasts of a model on the Y-axis (worse).
Main findings

- ‘Probabilistic’ SCARX models (nearly always) significantly outperform the Naive and ARX benchmarks
  - SCARX^Q models (nearly always) significantly outperform SCARX^H and SCARX^B

- Both averaging schemes generally significantly outperform the benchmarks and the non-combined SCARX models

- Averaging over probabilities (F-Ave^n) generally yields better probabilistic EPFs than averaging over quantiles (Q-Ave^n)

- In contrast to typically encountered economic forecasting problems (Lichtendahl et al., 2013)
Agenda

1. Beyond point forecasts ⇒ probabilistic forecasts
2. Combining forecasts
   - Point forecasts
   - Probabilistic forecasts
3. Seasonal components & short-term forecasting
   - SCAR framework
   - Case study
4. New trends in energy forecasting
4. New trends in energy forecasting

Point → 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
4. New trends in energy forecasting

Intraday forecasting

Time of delivery (on 26 Dec 2015)

Time of trading

Price in EUR/MWh

Volumes in MWh

25 Dec 2015

26 Dec 2015

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A new book on EPF ... forthcoming in 2018

Rafał Weron, Florian Ziel

Forecasting Electricity Prices: A Guide to Robust Modeling

Chap. 1: The Art of Forecasting
Chap. 2: Markets for Electricity
Chap. 3: Forecasting for Beginners
Chap. 4: Forecasting for Intermediates
Chap. 5: Evaluating Models and Forecasts
Chap. 6: Forecasting for Experts