Recent advances in electricity price forecasting: A 2018 perspective

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My electricity load & price modeling/forecasting network

Many thanks to all co-authors!!!

Rafał Weron (PWr, Wrocław)

Recent advances in EPF

3.10.2018, S3 Seminar
... in North America and Australia
The workhorse of European power trading

The day-ahead market
Seasonality, mean-reversion and price spikes

[Graph showing daily POLPX spot price from 2013-01-01 to 2017-05-31 with significant spikes in 2016 and 2017.]
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)

Dane: TGE, PSE (GPI)
Grudzień 2016
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Supply and demand, renewables and negative prices

Source: Ziel & Steinert (2016, ENEECO)
Day-ahead point forecasting: Univariate ...
... or multivariate?
Electricity price for day $d$ and hour $h$:

$$Y_{d,h} = \beta_{h,1} Y_{d-1,h} + \beta_{h,2} Y_{d-2,h} + \beta_{h,3} Y_{d-7,h}$$

\text{autoregressive terms}

$$+ \beta_{h,4} Y_{d-1}^{\text{min}} + \beta_{h,5} Y_{d-1}^{\text{max}} + \beta_{h,6} Y_{d-1,24}$$

\text{non-linear effects}

$$+ \sum_{j=1}^{7} \beta_{h,j} + 6 D_j + \varepsilon_{d,h},$$

\text{end-of-day effect}

\text{weekday dummies}
... neural nets ...
... or deep neural nets (DNN)?
Variable (feature) selection using LASSO

(UNiejewski et al., 2016, Energies; Ziel & Weron, 2018, ENEECO)

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

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

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

Red ellipses – contours of the LS error function

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Recent advances in EPF

3.10.2018, S3 Seminar 14 / 36
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

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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 surveys the complexity of available solutions, their strengths and weaknesses, and threats that the forecasting tools offer or may encounter. It looks ahead and speculates on the directions EPF will or should take or stay. 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. New trends in energy forecasting
A new hype: Point → probabilistic forecasting
(ca. 7% of EPF papers)
(Very) recent reviews of probabilistic EPF

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

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Probabilistic mid- and long-term electricity price forecasting

Florian Ziel, Rick Steinert

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 prices.
1. Beyond point forecasts

Global Energy Forecasting Competition 2014
(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
- Evaluation based on the Pinball Score (‘discrete’ CRPS)

GEFCOM 2014 Load Forecasting
GEFCOM 2014 Price Forecasting
GEFCOM 2014 Wind Forecasting
GEFCOM 2014 Solar Forecasting
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
- For an aggregate score average:
  - across all hours in the test period
  - across different 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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Point forecast averaging: The idea

Weights estimation

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

Individual forecasts

\[ f_1 \]
\[ f_2 \]
\[ \ldots \]
\[ f_N \]

Combined forecast

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!
Quantile Regression Averaging (QRA)

(Submitted on 31.12.2013, 21:26 ;-)

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 $q=0.05$ & $0.95$)

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

\[ X_t = [1, \hat{y}_{1,t}, ..., \hat{y}_{m,t}] \]

\[ \beta_q - \text{vector of parameters} \]

[\hat{y}_t^L, \hat{y}_t^U]
Quantile regression
Quantile regression

- Linear regression
- Quantile regression, $\alpha = 0.95, \alpha = 0.05$

Interval forecast

$q = 50\%$
$q = 25\%$
$q = 5\%$

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Recent advances in EPF
3.10.2018, S3 Seminar
FQRA: When the number of predictors is large
(Maciejowska, Nowotarski & Weron, 2016, IJF)

Individual point forecasts

\[
\hat{y}_{1,t}, \hat{y}_{2,t}, \ldots, \hat{y}_{m,t}
\]

PCA

\[
\hat{f}_{1,t}, \hat{f}_{2,t}, \ldots, \hat{f}_{k,t}
\]

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)

\[
[\hat{y}_t^L, \hat{y}_t^U]
\]
Combining probabilistic forecasts is more tricky

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

- **Average quantile forecast:** \( \text{Q-Ave}_n^* \equiv \hat{Q}^{-1}(x) \)
  with \( \hat{Q}(x) = \frac{1}{n} \sum_{i=1}^{n} \hat{Q}_i(x) \) and quantile forecast \( \hat{Q}_i(x) = \hat{F}_i^{-1}(x) \)
  \( \Rightarrow \) a horizontal average (always ‘sharper’ = ‘more concentrated’)

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### Averaging probabilities

![CDF Plot](image1)

- SCARX\(_Q^{HP5e10}\)
- SCARX\(_Q^{S6}\)
- F-Ave\(_Q^2\)

### Averaging quantiles

![CDF Plot](image2)

- SCARX\(_Q^{HP5e10}\)
- SCARX\(_Q^{S6}\)
- F-Ave\(_Q^2\)
- Q-Ave\(_Q^2\)

### Comparison

![CDF Plot](image3)

- F-Ave\(_Q^2\)
- Q-Ave\(_Q^2\)
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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
INREC 2018 hype: Intraday forecasting

Price in EUR/MWh

Volumes in MWh

Time of delivery (on 26 Dec 2015)

Time of trading

25 Dec 2015

26 Dec 2015

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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?

- Log(price)
- LTSC

- Log(price) - LTSC
LTSC and short-term price forecasting cont.

On the importance of the long-term seasonal component in day-ahead electricity price forecasting

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

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

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Variance stabilizing transformations (VSTs)
(Uniejewski, Weron & Ziel, 2018, IEEE-TPWRS)
Averaging across calibration windows

(Hubicka et al., 2018, IEEE-TSE; Marcjasz et al., 2018, Energies)