Enhancing load, wind and solar generation forecasts in day-ahead forecasting of spot and intraday electricity prices

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Introduction: A Small RES Producer

- Uncertainty: Weather dependency
- Price taker: Trades through a larger company
- Decision: Sell in the day-ahead or intraday market
- Objective: Maximize profits
Introduction

The Sign of The Price Spread

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Article

Day-Ahead vs. Intraday—Forecasting the Price Spread to Maximize Economic Benefits

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Abstract: Recently, a dynamic development of intermittent renewable energy sources (RES) has been observed. In order to allow for the adoption of trading contracts for unplanned events and changing weather conditions, the day-ahead markets have been complemented by intraday markets; in some countries, such as Poland, balancing markets are used for this purpose. This research focuses on a small RES generator, which has no market power and sells electricity through a larger trading
Research Problems

- Improving TSO (Transmission System Operator) load, wind and solar predictions
- Examining the impact on price forecasts
- Generating additional profit
Workflow

Forecasting load, wind & solar → Forecasting electricity prices → Forecasting the price spread
## Data for Germany: Notation

<table>
<thead>
<tr>
<th>Data</th>
<th>Notation</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day-ahead prices</td>
<td>$DA$</td>
<td>EUR/MWh</td>
</tr>
<tr>
<td>Intraday prices</td>
<td>$ID$</td>
<td>EUR/MWh</td>
</tr>
<tr>
<td>Load</td>
<td>$L$</td>
<td>GWh</td>
</tr>
<tr>
<td>Wind generation</td>
<td>$W$</td>
<td>GWh</td>
</tr>
<tr>
<td>PV generation</td>
<td>$S$</td>
<td>GWh</td>
</tr>
<tr>
<td>Forecasted load</td>
<td>$FL$</td>
<td>GWh</td>
</tr>
<tr>
<td>Forecasted wind generation</td>
<td>$FW$</td>
<td>GWh</td>
</tr>
<tr>
<td>Forecasted PV generation</td>
<td>$FS$</td>
<td>GWh</td>
</tr>
</tbody>
</table>
Electricity Prices (DA, ID)

Day-ahead - Germany

Intraday - Germany

Tomasz Weron et al. (Wrocław, PL) Enhancing forecasts December 13, 2019
Fundamental Variables ($L, W, S$)
### TSO (Transmission System Operator) Forecasts

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Peak</th>
<th>Off-peak</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Load</td>
<td>Wind</td>
</tr>
<tr>
<td>Mean</td>
<td>−2.767</td>
<td>0.756</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>LB test</td>
<td>12</td>
<td>12</td>
</tr>
</tbody>
</table>

- Standard deviations of the mean estimators are in brackets.
- Ljung-Box (LB) test verifies the autocorrelation of residuals, for each hour separately.
- Last row indicates the number of hours from the 12h peak/off-peak blocks, where the null is rejected at the 5% significance level.
Improving TSO Forecasts

Forecasting load, wind & solar

Forecasting electricity prices

Forecasting the price spread

Load

Generation [MWh]

Date

31-Dec-2014 01-Jan-2016 01-Jan-2017 02-Jan-2018

Tomasz Weron et al. (Wrocław, PL)
Forecasting Load ($L$)

$$L_{t,h} = \alpha_h D_t^L + \theta_{h,1}^L L_{t-1,h}^* + \sum_{p \in \{2,7\}} \theta_{h,p}^L L_{t-p,h}$$

- **AR component**
  $$+ \beta_{h,1}^L FL_{t,h} + \beta_{h,2}^L FW_{t,h} + \beta_{h,3}^L FS_{t,h}$$

- **Forecasts of fundamentals**
  $$+ \beta_{h,4}^L FL_{t,ave} + \beta_{h,5}^L FL_{t,max} + \beta_{h,6}^L FL_{t,min} + \varepsilon_{t,h}^L$$

- **Daily characteristics of load forecasts**
  $$L_{t-1,h}^* = \begin{cases} L_{t-1,h} & \text{if } h \leq 10 \\ FL_{t-1,h} & \text{if } h > 10 \end{cases}$$
Forecasting Wind and Solar Generation ($W$, $S$)

\[
W_{t,h} = \alpha_h^W D_t^W + \theta_h^W W_{t-1,h}^* + \beta_{h,1}^W FW_{t,h} + \beta_{h,2}^W FW_{t,ave} + \varepsilon_{t,h}^W
\]  (2)

\[
W_{t-1,h}^* = \begin{cases} 
W_{t-1,h} & \text{if } h \leq 10 \\
FW_{t-1,h} & \text{if } h > 10
\end{cases}
\]

\[
S_{t,h} = \alpha_h^S D_t^S + \theta_h^S S_{t-1,h}^* + \beta_{h,1}^S FS_{t,h} + \beta_{h,2}^S FS_{t,ave} + \varepsilon_{t,h}^S
\]  (3)

\[
S_{t-1,h}^* = \begin{cases} 
S_{t-1,h} & \text{if } h \leq 10 \\
FS_{t-1,h} & \text{if } h > 10
\end{cases}
\]
Forecast Averaging
Marcjasz et al., 2018; Hubicka et al., 2019

\[
\hat{X}_{t,h} = \frac{1}{\#\tau} \sum_{\tau} \hat{X}_{t,h}^\tau
\]  

\(\tau \in \{56, 82, 108, 134, 160, 186\} \cup \{330, 337, 344, 351, 358, 365\}\)
Forecast Validation

Root Mean Squared Error:

$$RMSE = \sqrt{\frac{1}{T} \frac{1}{24} \sum_{t=1}^{T} \sum_{h=1}^{24} \left( \hat{X}_{t,h} - X_{t,h} \right)^2}$$

Mean Absolute Error:

$$MAE = \frac{1}{T} \frac{1}{24} \sum_{t=1}^{T} \sum_{h=1}^{24} \left| \hat{X}_{t,h} - X_{t,h} \right|$$
## Improved TSO Forecasts: Results for 2016 & 2017

<table>
<thead>
<tr>
<th>Variable</th>
<th>Load</th>
<th>Wind</th>
<th>Solar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>2016</td>
<td>2017</td>
<td>2016</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>MAE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TSO</td>
<td>6.888</td>
<td>5.901</td>
<td>3.867</td>
</tr>
<tr>
<td>(p-val)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td><strong>RMSE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TSO</td>
<td>9.325</td>
<td>7.875</td>
<td>5.885</td>
</tr>
<tr>
<td>Model</td>
<td>7.299</td>
<td>5.945</td>
<td>5.630</td>
</tr>
<tr>
<td>(p-val)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Note: p-values of the Diebold-Mariano test of equal forecast accuracy with autocorrelation of order 7 and 2 for load and RES, respectively.
Forecasting Prices

- Forecasting load, wind & solar
- Forecasting electricity prices
- Forecasting the price spread

Day-ahead - Germany

Price [EUR/MWh]

-50 0 50 100

31-Dec-2014 01-Jan-2016 01-Jan-2017 02-Jan-2018

Date
Forecasting Day-ahead (DA) Prices

\[ DA_{t,h} = \alpha_h D_t + \sum_{p \in \{1,2,7\}} \theta_{h,p} DA_{t-p,h} \]

\[ + \beta_{h,4} DA_{t-1,ave} + \beta_{h,4} DA_{t-1,min} + \beta_{h,5} DA_{t-1,max} \]

\[ + \beta_{h,6} DA_{t-1,24} + \theta_{h,1} \hat{L}_{t,h} + \theta_{h,2} \hat{W}_{t,h} + \theta_{h,3} \hat{S}_{t,h} + \epsilon_{t,h} \]
Forecasting Intraday ($ID$) Prices: Model (6)

\[ ID_{t,h} = \alpha_h D_t + \theta_{h,1} ID^*_{t-1,h} + \sum_{p \in \{2,7\}} \theta_{h,p} ID_{t-p,h} \]

AR component

\[ + \beta_{h,4} DA_{t-1,ave} + \beta_{h,4} DA_{t-1,min} + \beta_{h,5} DA_{t-1,max} \]

Daily characteristics of day-ahead prices

\[ + \beta_{h,6} DA_{t-1,24} + \theta_{h,1} \hat{L}_{t,h} + \theta_{h,2} \hat{W}_{t,h} + \theta_{h,3} \hat{S}_{t,h} + \varepsilon_{t,h} \]

Last known price Forecasts of fundamentals

\[ ID^*_{t,h} = \begin{cases} ID_{t,h} & \text{if } h \leq 10 \\ DA_{t,h} & \text{if } h > 10 \end{cases} \]
Forecasting Intraday (ID) Prices: Model (7)

\[ ID_{t,h} = \alpha_h + \beta_{h,1}DA_{t,h} + \beta_{h,2}ID_{t-1,h} + \theta_{h,1}\hat{X}_{t,h} \]
\[ + \theta_{h,2}(\hat{X}_{t,h} - FX_{t,h}) + \theta_{h,3}(\hat{X}_{t-1,h} - FX_{t-1,h}) + \varepsilon_{t,h} \]  
(7)

Forecast errors of fundamentals

\[ ID^*_t,h = \begin{cases} 
ID_{t,h} & \text{if } h \leq 10 \\
DA_{t,h} & \text{if } h > 10 
\end{cases} \]
## Forecasted Prices: Results for 2017

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model</th>
<th>Measure</th>
<th>TSO</th>
<th>none</th>
<th>Enhanced</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>(5)</td>
<td>MAE</td>
<td>4.934</td>
<td>6.497</td>
<td>4.932</td>
<td>5.041</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.968)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSE</td>
<td>8.050</td>
<td>10.354</td>
<td>7.988</td>
<td>8.242</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>ID</td>
<td>(6)</td>
<td>MAE</td>
<td>6.818</td>
<td>8.044</td>
<td>6.771</td>
<td>6.453</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.080)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSE</td>
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<td>12.909</td>
<td>10.826</td>
<td>10.499</td>
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<tr>
<td></td>
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<td></td>
<td>(0.000)</td>
<td>(0.162)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSE</td>
<td>10.650</td>
<td>12.757</td>
<td>10.556</td>
<td>10.151</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
</tbody>
</table>

Note: p-values of the Diebold-Mariano test of equal forecast accuracy with autocorrelation of order 7
Forecasting the Price Spread

- Forecasting load, wind & solar
- Forecasting electricity prices
- Forecasting the price spread

Spread - Germany

Price [EUR/MWh]
-50 0 50 100

Date
31-Dec-2014 01-Jan-2016 01-Jan-2017 02-Jan-2018
Decision Making and Method Evaluation

Decision

\[ Y_{t,h} = \begin{cases} 
1 & \text{if } ID_{t,h} - DA_{t,h} > 0 \\
0 & \text{if } ID_{t,h} - DA_{t,h} \leq 0 
\end{cases} \]

Classification power

\[ p = \frac{1}{365} \frac{1}{24} \sum_{t=1}^{365} \sum_{h=1}^{24} 1_{\{Y_{t,h} = \hat{Y}_{t,h}\}} \]

Yearly profit over the benchmark (DA)

\[ \pi = \sum_{t=1}^{365} \sum_{h=1}^{24} \hat{Y}_{t,h} (ID_{t,h} - DA_{t,h}) \]
## Classification Power: Results for 2017

<table>
<thead>
<tr>
<th>Models</th>
<th>Correct classifications, $p$ (%)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DA</td>
<td>ID</td>
<td>TSO</td>
<td>none</td>
<td>Enhanced</td>
</tr>
<tr>
<td>Enhanced/Enhanced</td>
<td>(5)</td>
<td>(6)</td>
<td>51.3%</td>
<td>51.6%</td>
<td>51.6%</td>
</tr>
<tr>
<td></td>
<td>(5)</td>
<td>(7)</td>
<td>51.5%</td>
<td>50.2%</td>
<td>52.4%</td>
</tr>
<tr>
<td>TSO/Enhanced</td>
<td>(5)</td>
<td>(6)</td>
<td>51.3%</td>
<td>–</td>
<td>53.1%</td>
</tr>
<tr>
<td></td>
<td>(5)</td>
<td>(7)</td>
<td>51.5%</td>
<td>–</td>
<td>53.6%</td>
</tr>
</tbody>
</table>
## Additional Yearly Profit: Results for 2017

<table>
<thead>
<tr>
<th>Models</th>
<th>Profits, $\pi$ (EUR)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Enhanced/Enhanced</td>
<td>Enhanced/Enhanced</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(5)</td>
<td>(6)</td>
<td>(5)</td>
</tr>
<tr>
<td>DA ID</td>
<td></td>
<td>2326</td>
<td>1422</td>
<td>1827</td>
</tr>
<tr>
<td>TSO</td>
<td>none</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Enhanced</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TSO/Enhanced</td>
<td></td>
<td>(5)</td>
<td>(6)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2326</td>
<td>–</td>
<td>2320</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2050</td>
<td>–</td>
<td>2910</td>
</tr>
</tbody>
</table>
Conclusions

- TSO forecast errors can be reduced
  - Significant reduction for load ($L$)
  - Minor reduction for wind ($W$) and solar ($S$)
- Enhancing fundamentals improves price forecasts
  - Significant improvement for intraday ($ID$)
- Forecast errors of fundamentals are vital for intraday ($ID$)
  - Model (7) outperforms (6)
- The price spread can be determined successfully for each hour separately
  - TSO – 2 326 EUR
  - Enhanced – 3 123 EUR
  - Real – 10 898 EUR
Enhancing load, wind and solar generation forecasts in day-ahead forecasting of spot and intraday electricity prices

Katarzyna Maciejowska\textsuperscript{a}, Weronika Nitka\textsuperscript{b}, Tomasz Weron\textsuperscript{b}

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Abstract

In recent years, a rapid development of renewable energy sources (RES) has been observed across the world. Intermittent energy sources, which depend strongly on weather conditions, induce additional uncertainty to the system and impact the level and variability of electricity prices. Predictions of RES, together with the level of demand, have been recognized as one of the most important determinants of future electricity prices. In this research, it is shown that forecasts of these fundamental variables, which are published by Transmission System Operators (TSO), are biased and could be improved with simple regression models. Enhanced predictions are next used for forecasting of spot and intraday prices in Germany. The results indicate that improving the forecasts of fundamentals does not bring any gains in case of the spot market, but leads to more accurate predictions of intraday prices. Finally, it is demonstrated that utilization of enhanced forecasts is helpful in a day-ahead choice of a market (spot or intraday) and results in a substantial increase of profits.

Keywords: Renewables, Electricity prices, Day-ahead market, Intraday market, Forecasting