HSC Research Report

HSC/15/06

A hybrid model for GEFCom2014 probabilistic electricity price forecasting

Katarzyna Maciejowska[1,2]
Jakub Nowotarski[1,3]

[1] Department of Operations Research, Wrocław University of Technology, Poland
[2] CERGE-EI, Prague, Czech Republic
[3] Energy Production and Infrastructure Center, University of North Carolina at Charlotte, USA

Hugo Steinhaus Center
Wrocław University of Technology
Wyb. Wyspiańskiego 27, 50-370 Wrocław, Poland
http://www.im.pwr.wroc.pl/~hugo/

A hybrid model for GEFCom2014 probabilistic electricity price forecasting

Katarzyna Maciejowska[a,b], Jakub Nowotarski[a,c]

[a]*Department of Operations Research, Wrocław University of Technology, Wrocław, Poland*
[b]*CERGE-EI, Prague, Czech Republic*
[c]*Energy Production and Infrastructure Center, University of North Carolina at Charlotte, USA*

Abstract

This paper provides detailed information on Team Poland's approach in the electricity price forecasting track of GEFCom2014. A new hybrid model is proposed, consisting of four major blocks: point forecasting, pre-filtering, quantile regression modeling and post-processing. This universal model structure enables independent development of a single block, without affecting performance of the remaining ones. The four-block model design in complemented by including expert judgements, which may be of great importance in periods of unusually high or low electricity demand.

Keywords: Probabilistic forecasting, Hybrid model, Quantile regression, Electricity spot price, Forecasts combination, Pinball function

1. Introduction

Over the last decades, electricity spot price forecasting has became crucial for energy companies, in particular for operational management and short/mid - term planning. In the literature, various forecasting methods have been discused, among which statistical/econometric approaches (like multiple regressions, AR, ARIMA, AR-GARCH, jump-diffusions, factor models and regime-switching models) and computational intelligence techniques (like neural networks, fuzzy techniques and support vector machines) constitute the two main streams (see e.g. Hong, 2014; Weron, 2006).

The problem of electricity spot price point forecasts (i.e. the 'best guess' or expected value of the spot price) has been widely discussed so far, see Weron (2014) for a recent comprehensive review. On the other hand, probabilistic – i.e. interval and density – forecasts have been barely touched in the literature. This is even despite the fact that prediction intervals (PI), and density forecasts even more, provide more comprehensive information which makes them more useful in practice. Chatfield (2000) mentions several points supporting the importance of interval forecasts: (i) assessment of future uncertainty, (ii) ability to plan different strategies for the range of possible outcomes indicated by the interval forecast, and (iii) possibility of more thorough forecasts comparison. Also electrical engineers recognize high-quality prediction intervals of the market clearing price as benefitial for low-risk bidding (Amjady and Hemmati, 2006).

Despite this awareness, the literature on probabilistic forecasting is very scarce, a possible reason for which may be that the task becomes more challenging compared to point forecasting.

The aim of the paper is to present the novel methodology for electricity spot price probabilistic forecasting. The result of the presented model were verified during the price track in Global Energy Forecasting Competition 2014. The remainder of the article is structured as follows. In Section 2 we describe problem statement and discuss briefly probabilistic forecasting fundamentals. In Section 3 we present our methodology for computing the predictions, then in Section 4 we report our results. This is

Email addresses: `katarzyna.maciejowska@pwr.edu.pl` (Katarzyna Maciejowska), `jakub.nowotarski@pwr.edu.pl` (Jakub Nowotarski)

followed by discussion on the model's strengths and limitations as well as on possible improvements. Finally, Section 6 concludes the article.

2. Problem statement

To define the probabilistic forecast problem let us start with a point, one-step-ahead forecast of the electricity price. Regardless of the methodology used, this can be expressed as:

$$P_t = P_{t|t-1} + \varepsilon_t, \tag{1}$$

where P_t is the actual electricity price at time t, $P_{t|t-1}$ is its one-step ahead forecast and ε_t is the corresponding error. There are many methods, which can be used for constructing prediction intervals at the confidence level $(1-\alpha)$. The most popular is the one which uses both $P_{t|t-1}$ and ε_t (Weron, 2014). The interval center is set equal to the point forecast $P_{t|t-1}$, while its bounds are defined by the quantiles $\frac{\alpha}{2}$-th and $(1-\frac{\alpha}{2})$-th of the probability distribution of ε_t. This way of estimating PI, underlines the importance of the point forecast in deriving prediction quantiles.

A probabilistic forecast corresponding to the eq. (1) can be regarded as a set of PIs for all $\alpha \in (0,1)$. In other words, computing a probabilistic forecast requires estimation of $P_{t|t-1}$ and density f_{ε_t} of the corresponding error term, ε_t. Although we expressed the problem in terms of the probability density function, it can be equivalently formulated in terms of the inverse of the cumulative distribution function, F^{-1}:

$$q_t^\tau(P) = P_{t|t-1} + q_t^\tau(\varepsilon), \tag{2}$$

where $q_t^\tau(X) = F_{X_t}^{-1}(\tau)$ is the τ-quantile of P_t (or ϵ_t).

We should also note that some authors use the term confidence interval instead of prediction interval (PI), which might be confusing. However, in most forecasting applications our interest is the PI associated with a random variable (here: electricity price) which is to be observed, i.e. intervals which contain the true values of future observations with specified probability, not in confidence intervals associated with a parameter of a model, see Hyndman (2013) for a discussion.

2.1. GEFCom2014

The objective of the GEFCom2014 competition was to forecast 99 quatiles of the next day electricity prices, as an approximation of their forecast distribution. The entries were evaluated according to the so-called pinball function. For quantile $q_{h,t}^\tau$ of electricity spot price $P_{h,t}$, where h is the hour and t is the day index, the pinball function is defined as follows:

$$L_{h,t}(\tau) = \tau(P_{h,t} - q_{h,t}^\tau)\mathbb{I}_{P_{h,t} \geq q_{h,t}^\tau} + (1-\tau)(q_{h,t}^\tau - P_{h,t})\mathbb{I}_{P_{h,t} < q_{h,t}^\tau}, \tag{3}$$

where $\mathbb{I}$ is the indicator function. The final score for day t was computed as an average of $L_{h,t}(\tau)$ across 24 hours ($h = 1, ..., 24$) and 99 quantiles ($\tau = 0.01, ..., 0.99$).

The dataset available to GEFCom2014 participants consisted consists of three time series at hourly resolution: locational marginal prices, zonal loads and system loads. For the first regular (i.e. non-trial) competition week almost 2.5 years of historical prices were available. The information set was being extended and in the last week of the contest it was almost 3-years long, see Figure 1. For each of the 12 next day electricity price forecasts the actual day-ahead values of loads were known. Out of the 12 target days, 9 were from July 2013 (4th, 9th, 13th, 16th, 18th, 19th, 20th, 24th and 25th) and 3 from December 2013 (7th, 8th and 17th). The prices for those days are depicted in the Figure 2 in Section 4. For more competition details see Hong et al. (2015).

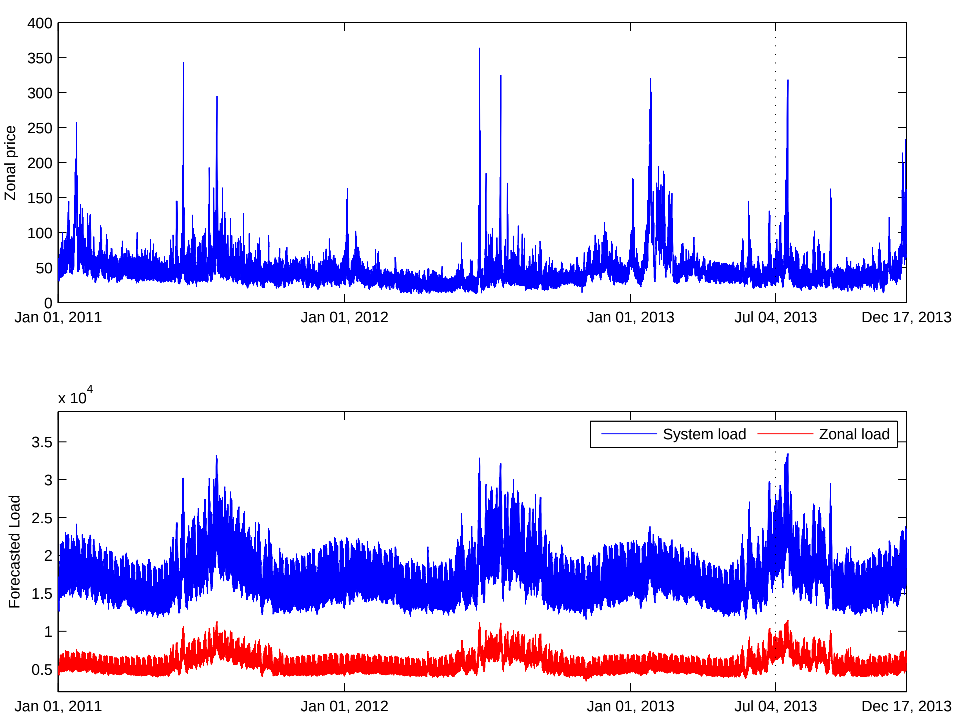

Figure 1: Hourly zonal price and hourly system and zonal loads, for the period Jan 01, 2011 – Dec 17, 2013. The vertical dotted line represents the beginning of the competition, i.e. the day from Task 4 (the first non-trial day).

3. The model

In this study, we propose a hybrid model with four major blocks: (i) point forecasting and averaging/ensembling, (ii) pre-filtering, (iii) quantile regression modeling and (iv) post-processing. We believe that the proposed methodology is not only interesting because of its good performance in the competition, but may also be appealing to practitioners because of its relative simplicity and modular structure. Even if it is not a *Keep It Simple* model, the statistical techniques used are not far from basic and standard approaches. Moreover, it can be easily adapted to multiple scenarios, for instance, high and low demand days. That said, we believe that the model is an interesting compromise between simplicity, flexibility and accuracy.

3.1. Model setup

As stated above, the modeling approach consists of four steps or blocks. It is based on the decomposition of the price process P_t into its point forecast and the forecast error, as in eq. (1). The 99 percentiles (i.e. quantiles for $\tau = 0.01, 0.02, \ldots, 0.99$) of the density forecast are computed according to eq. (2). In the first step, the point forecasts $\widehat{P}_{h,t|t-1}$, $h = 1, \ldots, 24$ are computed using historical prices and loads ($t = 1, ..., T$). It should be mentioned, that within the sample (for $t = 1, ..., T$) the forecasts correspond to the fitted values, whereas for $t = T + 1$ they become true out-of-sample forecasts. Since the shape of the distribution of the forecast error depends strongly on the accuracy of the point prediction, we treat this part with a lot of care, see Section 3.2. Next, we compute the errors $\widehat{\varepsilon}_{h,t} = P_{h,t} - \widehat{P}_{h,t|t-1}$ for $t = 2, ..., T$. The forecast error $\widehat{\varepsilon}_{h,T+1}$ is not known, therefore we apply quantile regression (QR) to predict its distribution, see Section 3.4.

In order to increase the quality of forecasts, we perform pre-filtering and post-processing. The former allows us to select a calibration sample, which is similar to the forecasted day and hence improve the forecast accuracy, see Section 3.3. Post-processing, on the other hand, corrects some model deficiencies (like a possible non-monotonicity of the computed 99 quantiles) and smooths the marginal distributions for each hour, see Section 3.5. Additionally, both approaches introduce a structural way of incorporating expert opinions into the prediction process.

3.2. Point forecasts

In order to obtain one day-ahead point forecasts $\widehat{P}_{t|t-1}$, linear regression models are applied to the original and partly filtered data. It is well known that prices in different hours follow distinct data generating processes Weron (2014). Therefore, we construct 24 separate models to describe the behavior of electricity prices during the whole day. We assume that the hourly prices, $P_{h,t}$, follow an ARX process. The price and the load data are log-transformed. The ARX model is defined as follows:

$$P_{h,t} = \alpha^T X_t + \alpha_1 P_{h,t-1} + \alpha_2 P_{h,t-7} + e_t \tag{4}$$

where $X_t = [1, W_t, L_{h,t}, L_{h,t-1}, L_{h,t-7}, \frac{\min_h(L_{h,t})}{\max_h(L_{h,t})}]$ and e_t is a white noise. The following exogenous variables are included:

- deterministic variables: a constant and the a weekend dummy (W_t takes value one during the weekend and zero otherwise),
- current and lagged loads for a given hour h: $L_{h,t}$, $L_{h,t-1}$ and $L_{h,t-7}$,
- the ratio of the smallest load to the largest load for a given day t: $\frac{\min_h(L_{h,t})}{\max_h(L_{h,t})}$.

The model is estimated with Least Squares (LS). For the early night hours, from midnight to 4:00 AM, we utilize additional information about the last prices from the previous day. Hence X_t is extended to include $P_{23,t-1}$ and $P_{24,t-1}$ for these 4 hours.

Next, a second ARX model is fitted to pre-filtered data. Only those days are selected for calibration which have a similar load pattern to the forecasted day (see Section 3.3). In order to avoid estimation problems, in case of this ARX model the weekend dummy is removed from X_t.

On the basis of these two ARX models (with and without the pre-filtering), point forecasts $\hat{P}^{(1)}_{h,T+1}$ and $\hat{P}^{(2)}_{h,T+1}$ are computed. The results are next transformed back to the original units. The final forecast is the arithmetic average of these two quantities: $\hat{P}_{h,T+1} = \frac{\hat{P}^{(1)}_{h,T+1} + \hat{P}^{(2)}_{h,T+1}}{2}$. This simple averaging scheme was used since it was found to perform well for electricity spot prices, (see Nowotarski et al., 2013).

3.3. Pre-filtering

In the forecasting experiment, we implement three pre-filtering methods: (i) day type filtering, (ii) similar load profile filtering and (iii) expected bias filtering. The filtering is applied both to the dependent and independent variables. It should be mentioned that for constructing the point forecast, we apply only the similar load profile filtering. The remaining filtering schemes, i.e. (i) and (iii), were used in the quantile regression only.

The first approach to pre-filtering, the 'day type filtering', utilizes only days of the pre-specified type. For example, when we aim at forecasting a working day, we choose only working days. Similarly, if we focus on weekends, we use only weekend data.

The aim of 'similar load profile' filtering is to choose days with the load profile similar to the load profile of the forecasted day. To achieve it, we need to choose a measure of the distance between load profiles coming from different days. Here, the mean of the squared differences of loads is used. For a day t, the measure is constructed as follows:

$$MSE_t = \frac{1}{24} \sum_{h=1}^{24} (L_{h,t} - L_{h,T+1})^2 . \tag{5}$$

Next, the days are ordered according to MSE_t and 10% (or some other percentage) of days with the lowest MSE_t is chosen for further analysis.

The final filtering technique, 'expected bias filtering', opens the possibility to include expert opinions about the possible bias of the point forecast. It was particularly useful for days when the load was extraordinarily high, low or had an unusual profile. The approach uses the within sample errors, calculated as the difference between the true price $P_{h,t}$ and its fitted value $\hat{P}_{h,t}$: $\hat{\varepsilon}_{h,t} = P_{h,t} - \hat{P}_{h,t}$.

An expert chooses two values: a and b and filters out all of the observations which do not fall into the interval $(\bar{\varepsilon} - a\sigma_{\varepsilon}, \bar{\varepsilon} + b\sigma_{\varepsilon})$, where $\bar{\varepsilon}$ and σ_{ε} are the sample mean and standard deviation of the residuals $\hat{\varepsilon}_{h,t}$, respectively. In the case of a "typical" day, we chose symmetric intervals (for example $a = b = 3$). When the true values were believed to exceed the predictions then we set $a < b$. On the contrary, when the model was expected to overestimate the price level then we set $a > b$.

3.4. Quantile estimates

Having obtained the point predictions for all hours, we now need to compute the corresponding quantiles of the distribution of prediction errors. One reason in favour of quantile regression is that it focuses on estimating the conditional quantile of the dependent variable, in this case electricity prices $P_{h,t}$. The loss function in QR is defined as $\rho_\tau(u) = |u(\tau - \mathbb{I}_{(u<0)})|$, where $\tau \in [0, 1]$. It is well known that for a random variable Y minimising the expected loss function of $Y - u$ with respect to u leads to finding its τ-th quantile. Also, as Maciejowska et al. (2015) found, QR is an appealing tool for electricity price probabilistic forecasting.

Recall that in this study we apply the quantile regression to the prediction errors, $\widehat{\varepsilon}_{h,t}$. In the regression, we assume that conditional quantiles are linear functions of exogenous variables. The problem can be written as follows:

$$\hat{q}^{\tau}_{h,t}(\varepsilon|X) = X_{h,t}\beta_{\tau}, \tag{6}$$

where $\hat{q}^{\tau}_{h,t}(\varepsilon|\cdot)$ is the conditional τ-th quantile of the electricity spot price forecast error distribution, $X_{h,t}$ are the regressors (explanatory variables) and β_τ is a vector of parameters. Notice, that in this set-up the parameters β_τ are assumed to be constant over the hour dimension, h. Therefore a pooled regression is used to estimate the parameters of interest. This assumption was imposed due to the limited number of observations, which remain for analysis after pre-filtering.

Here, quantiles are conditioned on $X_{h,t} = [1, X^{(1)}_{h,t}, X^{(2)}_{h,t}]$, where $X^{(1)}_{h,t}$ are the variables associated with the load and $X^{(2)}_{h,t}$ are the expected price levels, both described in Sections 3.4.1 and 3.4.1, respectively. It should be noticed that if the forecast errors were characterized by identical distribution functions than all the variables but the constant would be redundant. Here, we allow the distribution function to change over time, to reflect both nonlinearities of the price generating process and heteroscedasticity (dependence of the price variance on some exogenous factors and the expected price level).

3.4.1. Load level

In the model, we utilize information about the load in three ways. First, we include the variable describing the load level for a particular hour, $L_{h,t}$. Since, the electricity price prediction error depends not only on the load for a particular hour but also on the daily load pattern, we include the average daily load, $\bar{L}_t$, computed as $\bar{L}_t = \frac{1}{24}\sum_{h=1}^{24} L_{h,t}$.

Finally, we incorporate a measure, $LP_{h,t}$, of how typical is the load profile, as compared to the previous days which were used for constructing the point forecast. The variable is constructed as follows: $LP_{h,t} = \left(\frac{L_{h,t}}{L_{h,t-1}}\right)\left(\frac{L_{h,t-7}}{L_{h,t-8}}\right)^{-1} = \frac{L_{h,t}L_{h,t-8}}{L_{h,t-1}L_{h,t-8}}$. Hence, the load variables are $X^{(1)}_{h,t} = [L_{h,t}, \bar{L}_t, LP_{h,t}]$.

3.4.2. Expected price level

We include two forecasted values $\hat{P}^{(1)}_{h,t}$, $\hat{P}^{(2)}_{h,t}$ and the average daily expected price $\bar{\hat{P}}_t$, where $\bar{\hat{P}}_t = \frac{1}{24}\sum_{h=1}^{24} \hat{P}_{h,t}$. We expect that the observations associated with higher price predictions will be characterized by higher risk, which in turns will reflected by wider prediction intervals. In order to account for

Table 1: The official results of Team Poland's entries to Price Forecasting Track i GEFCOM14 compared to the organizers' Benchmark. The numbers are calculated according to the pinball function. The star in the Task 4 represents the only week when additional entry was done because of a special-day case as it was the 4th of July, presumably a holiday.

	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10	Task 11	Task 12	Task 14	Task 14	Task 15
Team Poland	1.00*	1.82	1.19	2.82	7.56	4.21	2.60	1.05	1.24	4.06	1.08	3.07
Benchmark	4.03	7.97	5.70	22.32	38.34	44.23	18.22	31.57	42.95	2.86	3.20	22.38

non-linear relationships between the price and the risk, we include in the model also the square of the expected price $\hat{P}^2_{h,t}$. So, the price variables are $X^{(2)}_{h,t} = [\hat{P}^{(1)}_{h,t}, \hat{P}^{(2)}_{h,t}, \bar{\hat{P}}_t, \hat{P}^2_{h,t}]$.

3.5. Post-processing

We post-process the results for two reasons. First, we forecast each of the 99 percentiles separately, hence the estimation process does not ensure that they are in an ascending order. Therefore, for each hour, we sort the forecasted quantiles of electricity prices. Second, the τ-th quantile across hours may be bumpy, whereas we typically observe smooth evolution of prices over the day. Therefore, we use a moving average over a three hour window to smooth the results. In should be mentioned that in some cases this part of post-processing is unnecessary. For example, in Task 15, we expected to have a one-hour spike, hence we could not apply the moving average because it will smoothed out the phenomenon. Finally, we allow experts to correct the results according to their experience by expanding or tightening the prediction intervals. This reflects their expectation about the forecasting and estimation risk. Experts, in some exceptional cases, were also allowed to incorporate other point forecasts of the mean or the median, which could not be included in the formal analysis described above.

4. Results

The results are summarized in Table 1. The outcomes indicate that some days involved more uncertainty than others and hence required additional effort. For example, Tasks 7-11 and Task 15 were characterized by a very low accuracy of the benchmark model (high values of the score function), which indicated an unusual behavior of prices. The difficulty in forecasting Tasks 8-9 and Task 15 were confirmed by high values of the score function obtained with our model.

The competition started with Task 4, which was a national holiday – July 4th, 2013. Because during national holidays the consumption and price patterns are different than during regular days, a special (simplified) version of the model had to be constructed and estimated.

Another interesting week from the forecasting perspective was Task 8. This was an extraordinary challenge since the forecasted zonal load for that day was historically the highest. Obviously this kind of peak load may trigger an electricity price spike but the problem was that it was hard to predict its magnitude. Moreover, from a statistical perspective this meant a great deal of uncertainty since throughout the calibration period there were no similar events. Recall that our model's prediction intervals stem from historical in-sample residuals and obviously this required additional forecasting precision. As a result, apart from using expected bias filtering, we decided to incorporate an expert decision and widen the intervals for the last ten quantiles (i.e. $\tau = 0.9, \ldots, 0.99$). What we did was rescaling the distance between each of these quantiles and the median by 1.5 times, see Figure 2. However, this change did not provide an appealing result for two reasons: (i) the expert change still included too little uncertainty and was done for too short period (from 3 PM instead of 2 PM) and (ii) the night hours were mis-predicted. The real price during the night was close to 5th percentile. However, this led to an evolution of our model – we realised that it needs to relate the early morning hours with the last hours of the previous day. As a consequence we introduced new variables in QR, namely $P_{23,t-1}, P_{24,t-1}$, see Section 3.2.

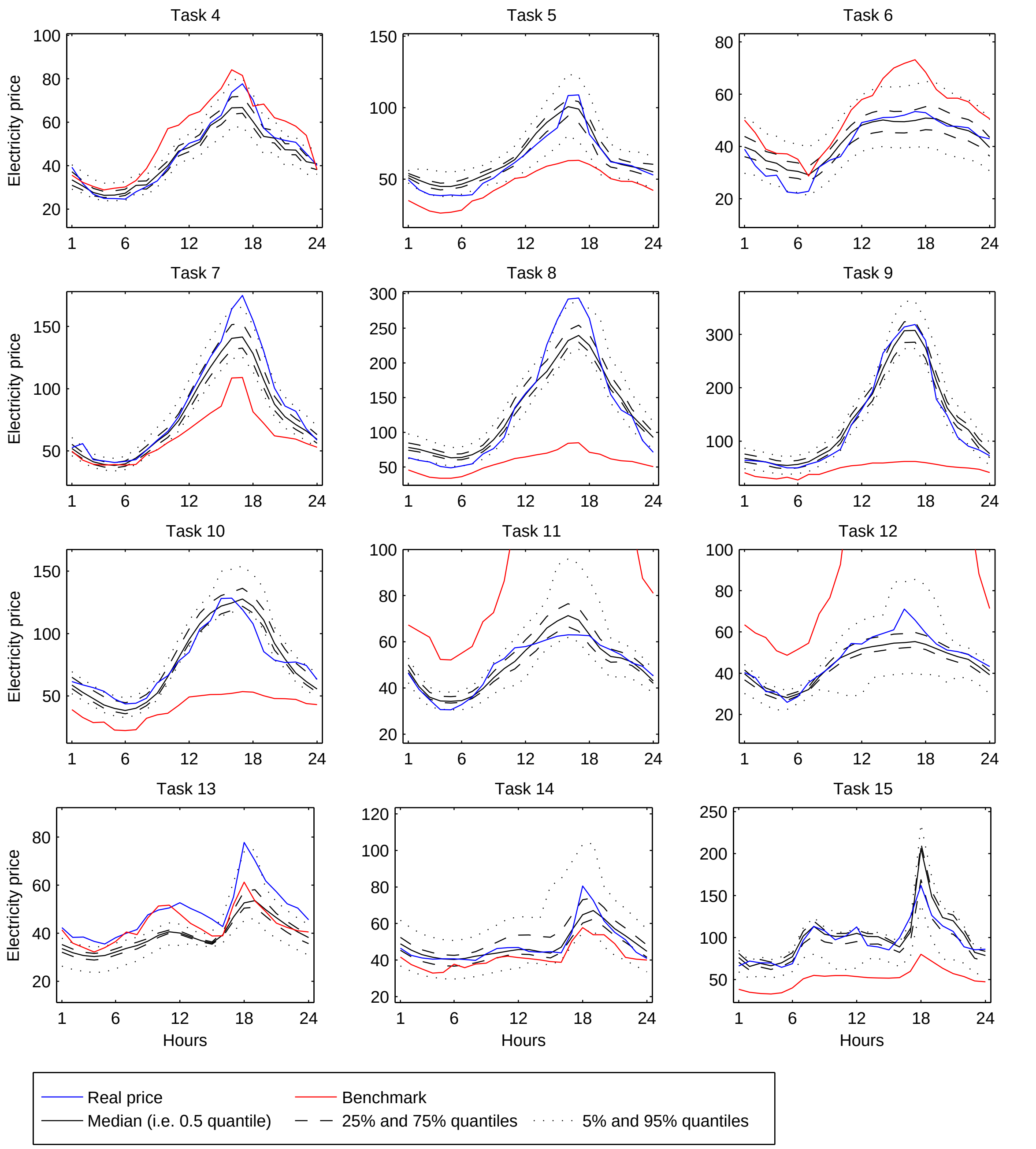

Figure 2: The results for all 12 competition tasks for both Team Poland (black lines) and the official Benchmark (red line). The true electricity prices are marked in blue.

Another week special enough to be discussed here was Task 9. This was similar to Task 8, meaning that once again a very high forecasted zonal load was given for that day. However, after the improvement discussed in the previous paragraph, we obtained much better results than a week before. The large score is in this case a result of very wide prediction intervals, since once again the uncertainty for the task was really high.

The next task we discuss is Task 13. Figure 2 shows clearly that our prediction was on a wrong level. The model we used for point forecasting underestimated the future values and ex-post analysis revealed that the distance between the Benchmark and our entry was similar to the distance between the Benchmark and the real price. What we obtained was clearly inaccurate. This was also the only week that we underperformed the Benchmark.

Finally, in the last week there was also a great concern about uncertainty and expected precision. One can see in Figure 2 that the intervals of our entry are quite wide, with the 5% quantile being far from the median and the lower quartile even for off-peak hours. The reason lies within the historical values – the preceding seven days exhibited extraordinary price behaviour. For 12th and 13th of December the price was peaking twice a day, including morning which had not happened at all during other days of that month. On the other hand, the last day of the information set, 16th of December, had just one price peak in the evening. Hence, three scenarios were possible – the two just mentioned and their mixture. We assumed a high level of uncertainty throughout the whole day, which was incorporated into pre-filtering. This resulted in the most accurate prediction of all competition participants for Task 15.

5. Discussion

5.1. Strengths and limitations

Although the model performed rather well and the obtained results allowed us to finish the competition on the second place, we observed some limitations. The main one was clear in Task 13, where we could not outperform the Benchmark. We claim this was almost entirely due to the inaccurate point forecast. However, it should be mentioned that such issues are inherent when constructing prediction intervals. One simply cannot correctly specify a model for all PIs – the real price, which lays outside the pre-constructed interval, has a given probability of occurrence. Hence, one of the possible reasons for this inaccuracy to happen is imperfect model for point prediction.

Another limitation of the model is independent of statistical methodology. We reported that Task 8 was particularly difficult since there were no similar historical values of the forecasted zonal load. In such cases the model presumably should be extended, for instance, using additional exogenous variables such as bidding information from a few previous days, merit order curve or data on generation and forecasted generation of renewables. This would allow a forecaster to see a better picture of future price uncertainty.

On the other hand, we believe that our methodology has a number of strong points. In general, the model being a compromise between flexibility and accuracy, enables a practitioner to adapt it easily to various market conditions while maintaining the desired quality of forecasts. Since the approach is not a pure *black-box* model it may incorporate experts opinions into the prediction process.

Moreover, the block design of the model enables improving each of the four parts separately. Even if the particular parts are related to each other, changes to them can be applied individually. Then, validation of this process is possible to find optimal specifications for all four blocks.

5.2. Further improvement

We still see some area where model improvements may be introduced. The main one is point forecasting. We used only two models and, as mentioned in Section 4, this has caused some troubles. The number of point forecasting methods is very large and this area of research is rather well-developed, so implementation of other methods is definitely a doable exercise.

On the other hand, with the increasing number of individual point forecasts, one may try other averaging schemes than the simple arithmetic average. For instance Nowotarski et al. (2013) analyse as many as 8 combining approaches, including performance-based, regression methods or bayesian model averaging. However, even if combining point forecasts has been discussed for over 45 years in the literature, there has been no clear evidence that an averaging method can consistently outperform the simple average.

6. Conclusion

In this paper we have discussed the methodology used by Team Poland in the Global Energy Forecasting Competition 2014 for the price track. The aim was to predict day-ahead densities at hourly resolution. While there is a number of studies on electricity price point forecasting, predicting the whole density has not been investigated thoroughly yet. For the contest, we developed a new methodology, the hybrid model consisting of four major blocks: point forecasting and averaging/ensembling, pre-filtering, quantile regression modeling and post-processing. One appealing aspect of the model is that it keeps a right balance between flexibility and accuracy and allows a forecaster to incorporate expert opinions into the prediction process.

The outcomes of the model make it an appealing tool for forecasting. It beat the Benchmark in 11 out of 12 tasks according to the score function defined by the organizers. Our model was evolving during the competition, but we believe that the end product could be utilized in many more scenarios than just price forecasting, for instance, in risk management and decision-making process.

Acknowledgments

Special thanks for critical comments and suggestions earlier versions of the manuscript go to Rafał Weron and Tao Hong. This work was supported by funds from the National Science Centre (NCN, Poland) through grant no. 2013/11/N/HS4/03649 (to J.N.).

References

Amjady, N., Hemmati, M. (2006) Energy price forecasting, IEEE Power & Energy Magazine, March/April, 20-29.

Chatfield, C. (2000) Time-Series Forecasting, Chapman & Hall/CRC, Boca Raton, Florida.

Hong, T. (2014) Energy forecasting: Past, present, and future. Foresight, Winter, 43-48.

Hong T., Pinson P., Fan S., Zareipour H., Troccoli A., Hyndman R. (2015) Probabilistic Energy Forecasting: State-of-the-art 2015. International Journal of Forecasting.

Hyndman, R. (2013) The difference between prediction intervals and confidence intervals, Hyndsight Blog (13 March 2013), http://robjhyndman.com/hyndsight/intervals.

Maciejowska, K., Nowotarski, J., and Weron, R. (2015) Probabilistic forecasting of electricity spot prices using factor quantile regression averaging. International Journal of Forecasting, doi: 10.1016/j.ijforecast.2014.12.004, 2015.

Nowotarski, J., Raviv, E., Trück, S., Weron, R. (2014) An empirical comparison of alternate schemes for combining electricity spot price forecasts. Energy Economics 46, 395-412.

Weron, R. (2014) Electricity price forecasting: A review of the state-of-the-art with a look into the future. International Journal of Forecasting 30(4), 1030-1081.

Weron, R. (2006) Modeling and Forecasting Electricity Loads and Prices: A Statistical Approach. Wiley, Chichester.

HSC Research Report Series 2015

For a complete list please visit http://ideas.repec.org/s/wuu/wpaper.html

01 *Probabilistic load forecasting via Quantile Regression Averaging on sister forecasts* by Bidong Liu, Jakub Nowotarski, Tao Hong and Rafał Weron

02 *Sister models for load forecast combination* by Bidong Liu, Jiali Liu and Tao Hong

03 *Convenience yields and risk premiums in the EU-ETS - Evidence from the Kyoto commitment period* by Stefan Trück and Rafał Weron

04 *Short- and mid-term forecasting of baseload electricity prices in the UK: The impact of intra-day price relationships and market fundamentals* by Katarzyna Maciejowska and Rafał Weron

05 *Improving short term load forecast accuracy via combining sister forecasts* by Jakub Nowotarski, Bidong Liu, Rafał Weron and Tao Hong

06 *A hybrid model for GEFCom2014 probabilistic electricity price forecasting* by Katarzyna Maciejowska and Jakub Nowotarski