Electricity price forecasting for Nord Pool data

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***Abstract*–Due to worldwide liberalization of power markets, electricity can be purchased and sold as any other commodity. The market spot price of electricity has features such as high volatility, seasonality and spikes. In order to minimize risks, maximize profits and make future plans, it is important for participants of electricity market to forecast future prices. The vast number of various methods is applied for solving this problem. However, the accuracy of forecasts is not sufficient, different approaches work differently with different countries (markets). In this paper we describe our experiments with electricity spot price data of Lithuania's price zone in *Nord Pool* power market. Short-term forecasts are made by using Average, Seasonal Naïve and Exponential smoothing methods, and results are reported.**

Keywords–electricity spot price; forecasting

I. INTRODUCTION

Nowadays electricity can be considered as any other commodity. It can be purchased, sold, traded under the rules of electricity market. This is the outcome of worldwide liberalization of power markets. In order to minimize risks, maximize profits and make plans, it is important for participants of electricity market to forecast future prices. For instance, using accurate short-term price forecasting, power suppliers can make bidding strategies, which would lead to higher profits. However, due to characteristics of electricity spot price such as high volatility, multiply seasonality and spikes, it is a challenging task to forecast accurately. Despite the large number of various methods which are applied for prediction of electricity spot prices, the accuracy of forecasts is not sufficient as various approaches work differently with distinct countries (markets).

In recent literature many of electricity price forecasting approaches are hybrid solutions, which combine two or more different methods. For instance, the proposed approach in [1] is a combination of adaptive-network based fuzzy inference system and particle swarm optimization. It is applied to forecast next-week prices in the electricity market of mainland Spain. For the sake of simplicity and clear comparison, no exogenous variables are considered. The forecasting accuracy is measured by using MAPE error which is 5.28 %.

Another example would be in [2] introduced hybrid intelligent algorithm utilizing a data filtering technique based on wavelet transform, an optimization technique based on firefly algorithm, and a soft computing model based on fuzzy ARTMAP network. This method is used to forecast day-ahead electricity prices in the Ontario market. Prognoses are made for 24 and 168 hour short-term horizons. The accuracy of method is measured by using MAPE, MAE errors as well as coefficient of determination. MAPE error, which is calculated for 24 hour horizon, varies from 6.24 % to 7.67 %.

A hybrid wavelet-ELM (Extreme Learning Machine) method is applied in [3]. Short-term forecasts are made for Ontario, PJM, Italy and New York Electricity markets. MAE, MAPE, MDE errors are chosen for evaluation of accuracy.

In [4] an econometric model for the hourly electricity price of the European Power Exchange for Germany and Austria is presented. The model, which can be regarded as a periodic VAR-TARCH, is proposed in order to capture the specific price movements. Wind power, solar power, and load are considered as factors which have influence on the price.

Out of literature by Lithuanian authors, there was only one master thesis on the topic of electricity

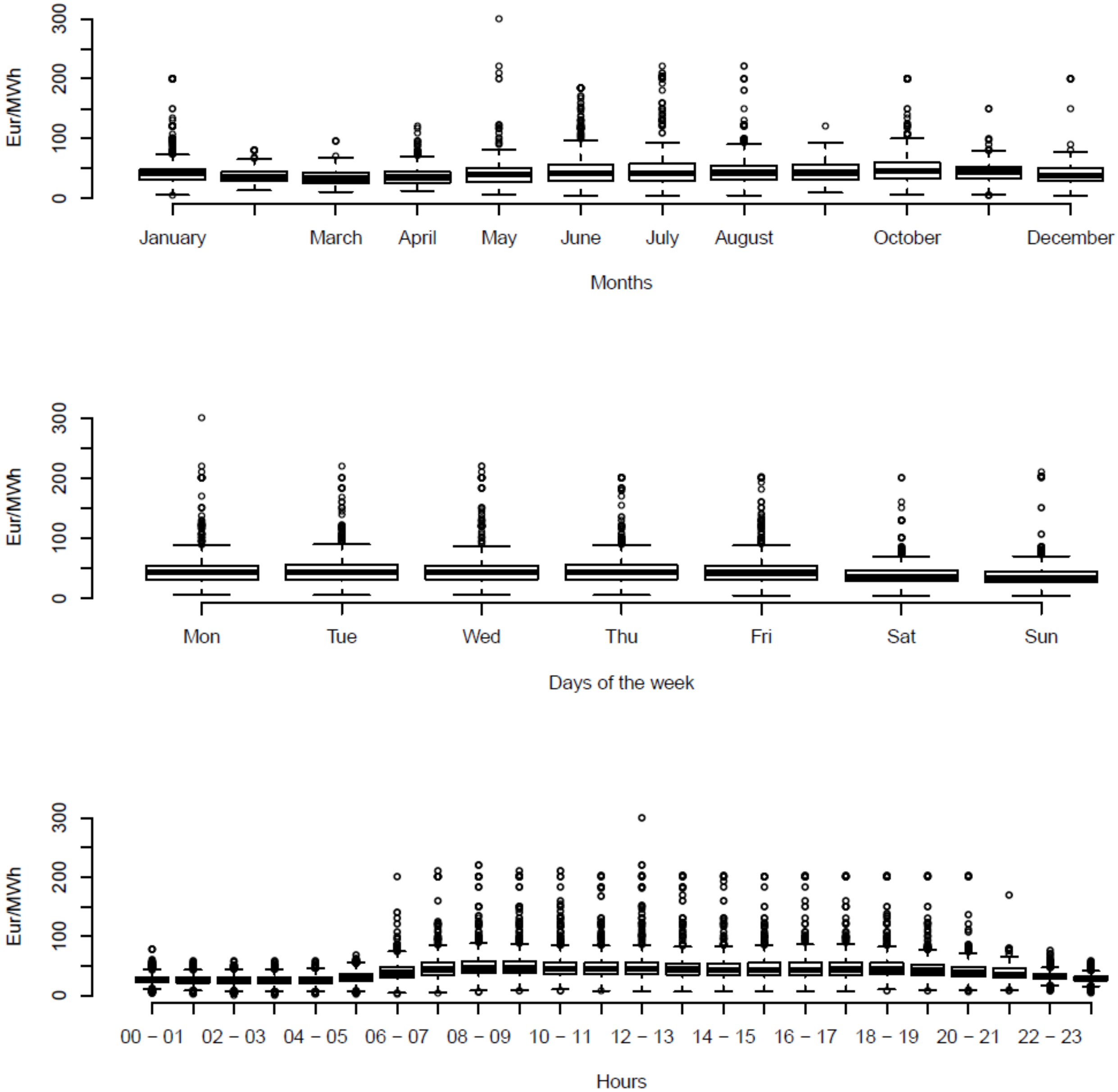

Figure 1. Boxplots of aggregated price data

price forecasting. Forecasts in [5] are made for France market using SARIMA-TGARCH and SARFIMA-TGARCH models.

In this paper we discuss application of short-term forecast using Average, Seasonal Naïve and Exponential smoothing methods to electricity spot price data of Lithuania's price zone in *Nord Pool* power market.

II. METHODS

Based on [6], models, applied for electricity price forecasting, can be classified into five broad groups:

1) multi-agent (Nash-Cournot framework, supply function equilibrium, strategic production-cost models, agent-based simulation models);
2) fundamental (parameter-rich fundamental models, parsimonious structural models);
3) reduced-form (jump-diffusion models, Markov regime-switching models);
4) statistical (similar-day and exponential smoothing methods, regression models, AR-type time series models, ARX-type time series models, threshold autoregressive models, heteroskedasticity and GARCH-type models);

5) computational intelligence (feed-forward neural networks, recurrent neural networks, fuzzy neural networks, support vector machines).

With multi-agent models price process is simulated by matching the demand and supply in the market. These models are considered as extremely flexible tools for the analysis of strategic behaviour in electricity markets. However, as they generally focus on qualitative issues, high accuracy of prediction cannot be achieved.

Fundamental techniques are used to characterize dynamics of electricity price by taking into consideration physical and economical factors, which may have impact on the price. There are two main problems while constructing such models. The first problem is the availability of information and data. The second problem concerns incorporation of stochastic fluctuations of fundamental factors.

Reduced-form approaches are used to describe statistical properties of electricity prices over time. The accuracy of forecasts using these models is not expected to be high. On the other hand, such models provide realistic description of electricity price dynamics and are commonly used for derivatives[1] pricing and risk analysis.

Using statistical models the forecast is made by mathematically combining previous prices. The accuracy of these models depends on efficiency of algorithms, quality of the data, ability to incorporate values of important exogenous factors. The main weakness of these methods is poor performance in the presence of price spikes.

Computational intelligence methods are flexible and can handle complexity as well as non-linearity. However, the ability to adapt to non-linear, spiky behaviours may not necessarily result in better point forecasts.

Factors

A number of factors can influence fluctuation of electricity prices. Due to the exogenous variables such as technical limitation and oil price, electricity generation capacity and cost are changing. Energy demand varies as well, and depends on the time of the day, weekday, season and weather conditions [7], e.g., during the hot summer day due to high usage of cooling systems, demand significantly increases. Uncertainty in factors such as weather, equipment outages, fuel prices, and transmission bottlenecks can cause extreme price volatility or spikes [3].

The supply of energy from renewable sources, especially solar and wind, rose significantly within the past years [4], hence it is also considered as an influential factor.

Historical electricity prices and demand data are considered to be the two of the main factors [7].

Forecasting Horizons

Electricity price forecasting can be categorized into three different categories based on time horizons. Nonetheless, there is no consensus in the literature as to what the thresholds should actually be. These categories are [6, 8]:

1) **Short-term forecasts** can involve forecasts from a few minutes up to a few days or a week. They are mainly used by the market players with the intention to maximize profits in the spot markets.
2) **Medium-term horizons** can be considered from a few days to a few months ahead. They might be preferred for balance sheet calculations, risk management and allow the successful negotiations of bilateral contracts between suppliers and consumers.
3) **Long-term forecasting** period can vary from few months up to few years. Such forecasts might influence the decisions on transmission expansion and enhancement, generation augmentation and distribution planning.

Measures of Accuracy

Point forecasts are used in majority of electricity price forecasting papers. Therefore, accuracy measures, which are based on absolute errors, are the mostly used. Error is defined as the difference between the actual value and the forecast value for the corresponding period. Due to easy interpretation, by far the most popular measure is the mean absolute percentage error (MAPE). Though, MAPE error might be misleading in the presence of close to zero prices [6, 8].

1) Mean Absolute Percentage Error

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

2) Mean Absolute Error or Mean Absolute Deviation

$$MAE = MAD = \frac{1}{n}\sum_{t=1}^{n}|F_t - A_t|.$$

3) Mean Squared Error

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2.$$

4) Root Mean Square Error

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2}.$$

[1] Financial contract with a value based on an underlying asset.

Here A_t is the real value and F_t – forecast value.

III. DATA

Data Set

In this paper data of Lithuania's price zone in Nord Pool power market is analysed. The data set consists of historical hourly electricity prices (Eur/MWh) from January 1, 2014 to December 31, 2016.

Data Analysis

Data set was analysed using descriptive statistics. In Table 1 and Figure 1 summary electricity price data is provided.

Statistical analysis shows that electricity price is lower on weekends compared to other days of the week. The price is also lower in winter and spring months, as well as on night hours of the day. In comparison to midday hours, there are much less outliers during the night hours. Moreover, these price spikes are less significant. The highest price peak, which reached 300 Eur, was on Monday. During summer months, there are much more spikes (which can be seen as outliers in the boxplot) than in other seasons of the year.

Table I
DESCRIPTIVE STATISTICS

Statistic	Value
N	26304
Mean	42.86
Median	40.76
Standard deviation	19.68
Variance	387.22
Minimum	4.02
Maximum	300

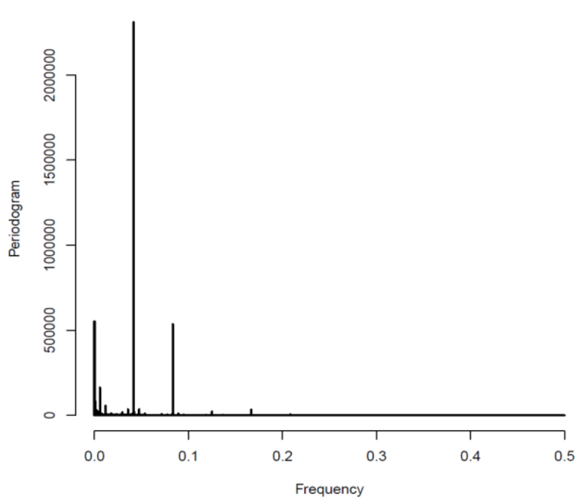

Figure 2. Periodogram of data set

For identification of the dominant periods (frequencies) of data set, periodogram [2] was used (Figure 2). Seasonality of daily (the highest spike in periodogram), annual (second most significant spike), 12-hour (third highest spike) and weekly (fourth highest spike) frequencies were detected.

IV. FORECASTING

Experimental results

Forecasting experiments were made for each day of the year 2016. Average, Seasonal Naïve and Seasonal Exponential smoothing methods were used for short-term day-ahead prognosis of total 24 points (description of these methods can be found in [9]). Daily seasonality was chosen as the most important in Seasonal Naïve method. Exponential smoothing was automatically selected using statistical package R. The accuracy was measured using RMSE, MAE and MAPE errors.

See summary of yearly results in Tables 2, 3 and 4.

Table II
SUMMARY OF YEARLY ERRORS. EXPONENTIAL SMOOTHING METHOD.

Statistic	RMSE	MAE	MAPE
Mean	**8.64**	**6.49**	**16.03**
Median	**5.76**	**4.53**	**12.18**
Standard deviation	10.46	7.10	11.43
Variance	109.37	50.48	130.68
Minimum	**0.83**	**0.69**	**1.76**
Maximum	94.02	70.96	95.04

Table III
SUMMARY OF YEARLY ERRORS. SEASONAL NAÏVE METHOD.

Statistic	RMSE	MAE	MAPE
Mean	9.36	6.70	16.6
Median	5.89	4.43	12.40
Standard deviation	11.83	7.86	13.87
Variance	139.90	61.74	192.28
Minimum	**1.02**	**0.66**	**1.91**
Maximum	100.2	76.48	118.0

Table IV
SUMMARY OF YEARLY ERRORS. AVERAGE METHOD.

Statistic	RMSE	MAE	MAPE
Mean	11.78	9.79	28.32
Median	8.82	7.72	25.19
Standard deviation	10.78	8.07	15.07
Variance	116.23	65.10	227.08
Minimum	**2.11**	**1.79**	**4.64**
Maximum	99.0	79.63	103.1

[2] An estimate of the spectral density of a signal.

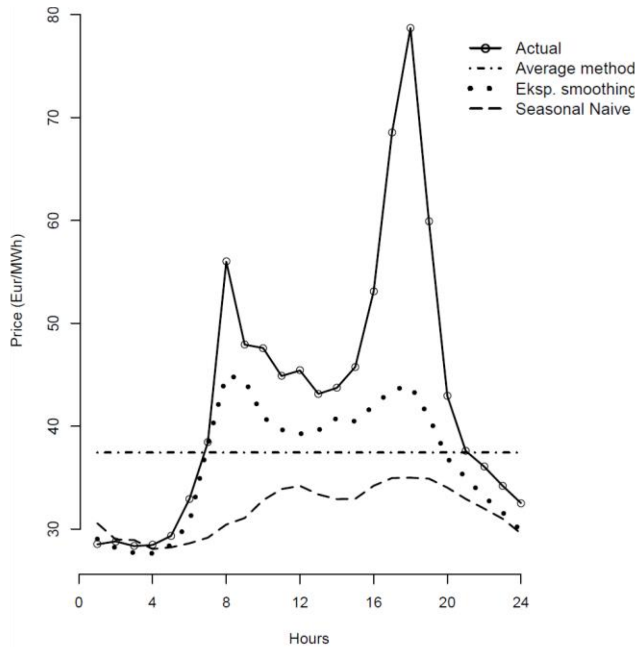

Figure 3. Forecasts for weekday in winter

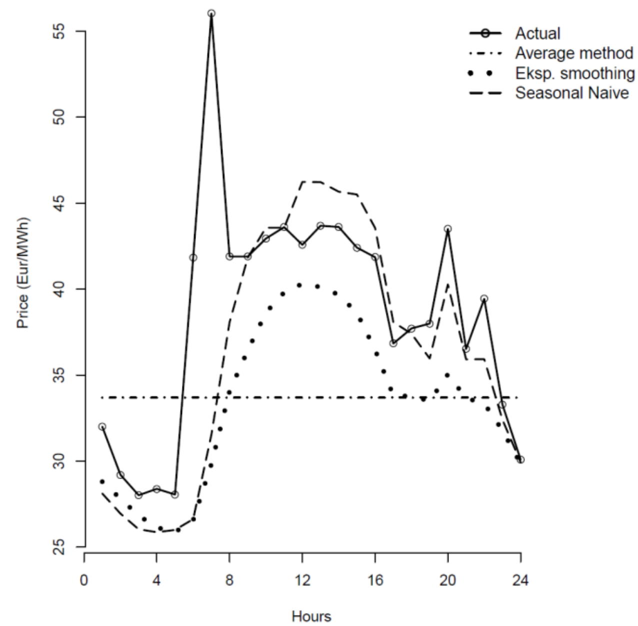

Figure 5. Forecasts for weekday in summer

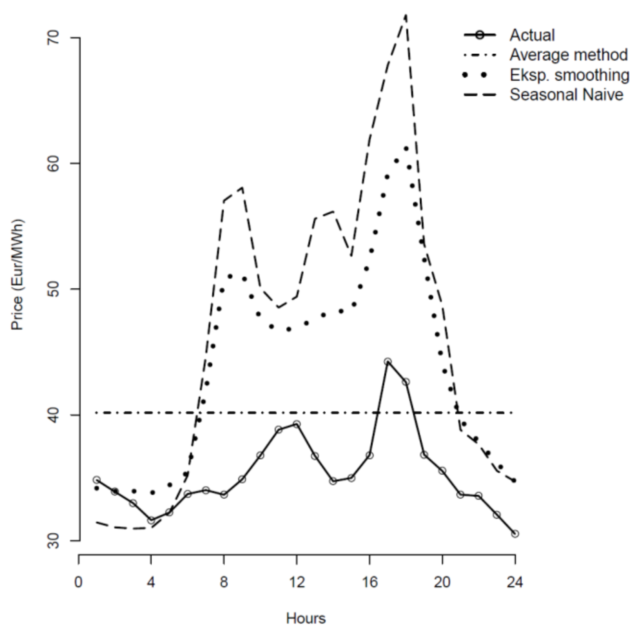

Figure 4. Forecasts for weekend in winter

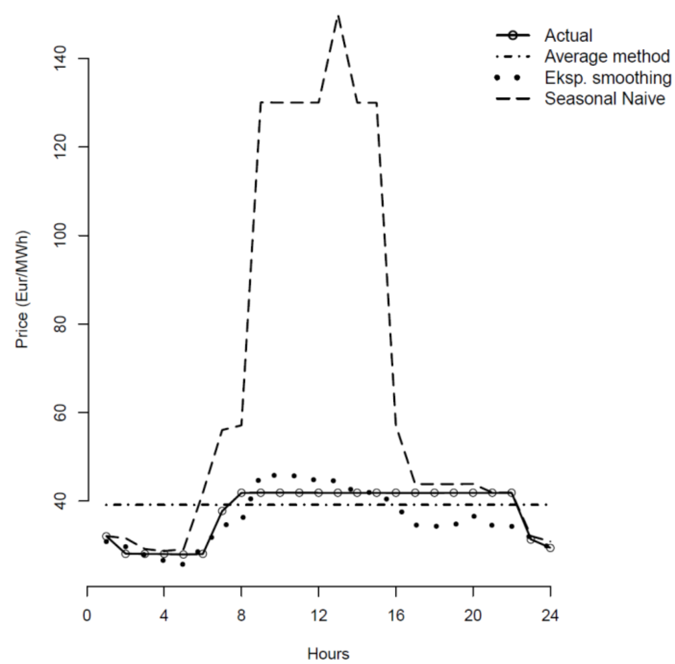

Figure 6. Forecasts for weekend in summer

The highest accuracy (considering all three measures of accuracy) was achieved using Exponential smoothing method. The lowest MAPE error was equal to 1.76%. However, average MAPE error of the year was 16.03% with standard deviation of 11.43%. As there are many outliers in the data, median of MAPE (which is equal to 12.18%) might better represent the typical error.

See forecasts for one work day and one weekend day of randomly chosen winter and summer weeks of 2016 in Figures 3, 4, 5 and 6. In Figure 6 significant difference between predicted prices and real values can be noticed. MAPE error of this day was equal to 72.67 %. In this case, predicted day was Saturday and there was prices spikes the day before. In Seasonal Naïve method each forecast is assumed to be equal to the last observed value from the same period.

Therefore, prognosis was extremely inaccurate. On the other hand, performance of Exponential smoothing method was quite accurate with MAPE error equal to 8.54% that day. Figures 3 and 5 show how all methods are unable to capture sudden price peaks. Only on winter weekend day (4 Figure), accuracy of Average method was highest according to MAPE error which was equal to 22.13%. However, RMSE and MAE errors of Exponential smoothing method for that day were lower.

V. CONCLUSIONS AND FUTURE WORK

Electricity price posses features such as high volatility and spikes. Even though there are many methods which can be used in electricity price forecasting, these features make it difficult to achieve high accuracy of forecasts. Therefore, in the recent literature mostly hybrid models are being suggested.

Analysis of Lithuania's price zone data shows that there is daily, weekly and annually seasonality patterns. Furthermore, prices tend to be lower in winter-spring months, at night and on weekends. Forecasting experiments show that simple statistical methods are not performing well when it comes to capturing spikes as well as transition from workday to weekend day and vice versa. The highest accuracy was achieved using Exponential smoothing method.

Future work plans are to search for the best approach for Lithuania's electricity price zone by testing more advanced statistical, machine learning and hybrid models, especially, including external data.

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