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Jakub Nowotarski^{*,**}

Jakub Tomczyk^{*,**}

Rafał Weron^{**}

* Hugo Steinhaus Center, Wrocław University of
Technology, Poland

** Institute of Organization and Management, Wrocław
University of Technology, Poland

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

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Abstract—We present the results of a study on modeling and forecasting of the long-term seasonal component (LTSC) of electricity spot prices. We consider a vast array of models including linear regressions, monthly dummies, sinusoidal decompositions and wavelet smoothers. We find that in terms of forecasting EEX and Nord Pool spot prices up to a year ahead, wavelet-based models significantly outperform all considered piecewise constant and sine-based models. This result challenges the traditional approach to deseasonalize spot electricity prices by fitting monthly dummies or sinusoidal functions. We also find that extending the calibration window up to four years does not improve the results; two- and especially three-year windows lead to better spot price forecasts.

Index Terms—Electricity spot price, Forecasting, Seasonality, Monthly dummies, Sinusoidal decomposition, Wavelets

I. INTRODUCTION

WHEN modeling electricity spot prices, one of the greatest challenges is to estimate and ultimately forecast the seasonal and deterministic trends in the data [16, 21, 26]. In day-ahead, or generally short-term forecasting the quality of seasonal decomposition does not play such an important role. However, in the mid-term (i.e., a few weeks to a few months) a badly predicted seasonal pattern will most likely do more harm than a misspecified stochastic model. And mid-term price forecasting is more important for risk management and simulation-based derivatives pricing of electricity derivatives than short-term forecasting. Surprisingly, in many academic papers the forecasting of the seasonal pattern has been overlooked or downplayed. With this paper we fill the gap and present a simulation study on estimation and forecasting of the long-term seasonal component (LTSC) of electricity spot prices.

The article is structured as follows. In Section II we review the seasonal decomposition techniques found in the electricity spot price modeling literature and comment on using them for forecasting the LTSC. Next, in Section III we describe the 129 models used in this empirical study. In Section IV we briefly introduce the datasets, the simulation setup and the error measures and in the following Section discuss the results. Finally, in Section VI we conclude and wrap up the results.

J. Nowotarski and J. Tomczyk are with the Hugo Steinhaus Center and the Institute of Organization and Management, Wrocław University of Technology, Wyb. Wyspiańskiego 27, 50-370 Wrocław, Poland. R. Weron is with the Institute of Organization and Management, Wrocław University of Technology, Wyb. Wyspiańskiego 27, 50-370 Wrocław, Poland.

E-mail addresses: jakub.nowotarski@gmail.com, jstomczyk@gmail.com, and rafal.weron@pwr.wroc.pl

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Matlab codes used in this article for the estimation and forecasting of the LTSC of electricity spot prices are available for download from the HSC IDEAS/RePEc repository: <http://ideas.repec.org/s/wuu/hscode.html>.

II. SEASONAL DECOMPOSITION OF ELECTRICITY SPOT PRICES

The standard approach to seasonal decomposition dates back to the 1950s and the *the Census I method* [20, 27]. The signal, in our case the electricity spot price time series P_t , is decomposed either in an additive or a multiplicative fashion into:

- the trend-cycle or long-term seasonal component (LTSC) T_t , representing the influence of such fundamental factors as fuel prices, seasons of the year and long-term bidding strategies,
- the periodic short-term seasonal component (STSC) s_t , used to describe the weekly pattern and
- the remaining variability or stochastic component X_t .

While the additive scheme (i.e., $P_t = T_t + s_t + X_t$) is more popular, note that if applied to logarithms of prices it is equivalent to the multiplicative specification (i.e., $P_t = T_t \cdot s_t \cdot X_t$) for the prices themselves.

The LTSC has been treated in the energy economics literature in a number of ways which, for convenience, can be divided into three classes:

- piecewise constant functions or dummies, possibly combined with a linear or an exponential trend [7, 8, 10, 11, 13, 18, 19],
- sinusoidal functions or sums of sinusoidal functions of different frequencies [1, 2, 4, 6, 9, 17, 19, 27, 28],
- wavelets [5, 14, 15, 23, 25, 27, 29, 30] or other nonparametric smoothing techniques [3].

Forecasting of a dummy-based LTSC is straightforward. However, this approach yields a non-smooth trend-seasonal component with jumps between months (usually a dummy is used for each month), which can cause difficulties when estimating the stochastic component. Also forecasting a sine-based LTSC is straightforward. Yet, except for a few regular periods like the Jan 1997 – Apr 2000 period at Nord Pool analyzed by [28], the LTSC cannot be modeled by a single sine function. Using a sum of a few sine/cosine functions is possible, see e.g. [4], but the usefulness of this approach is questionable since a regular annual periodicity can hardly be observed in electricity spot price data, see Figure 1. On the other hand, while the wavelet decomposition and smoothing is a more robust to outliers and a less periodic alternative to Fourier analysis, the forecasting of a wavelet-based LTSC is not trivial [14].

TABLE I
MODEL CODES

Digit	Value	Meaning
<i>All models</i>		
*□****	2	two year (730 day) calibration window
	3	three year (1095 day) calibration window
	4	four year (1460 day) calibration window
<i>21 simple linear and exponential models (1*000*)</i>		
1*000□	1	mean price in the calibration window
	2	extrapolated linear regression of prices in the calibration window
	3	median price in the calibration window
	4	exponential decay to the median with the decay parameter $\lambda = \frac{1}{30}$
	5	exponential decay to the median with the decay parameter $\lambda = \frac{1}{180}$
	7	mean-based monthly dummies
	8	median-based monthly dummies
<i>36 sine-based models (2***00)</i>		
2*□*00	1, ..., 4	number of sines used to represent the LTSC
2**□00	1	periods of all sines estimated
	2	period of the 1 st sine estimated, remaining periods set to 1, $\frac{1}{2}$ and $\frac{1}{3}$ of a year
	3	periods set to 1, $\frac{1}{2}$, $\frac{1}{3}$ and $\frac{1}{4}$ of a year
<i>72 wavelet-based models (4***0*)</i>		
4*□*0*	1	Daubechies wavelet family of order 12 ('db12')
	2	Daubechies wavelet family of order 24 ('db24')
	3	Coiflets wavelet family of order 2 ('coif2')
	4	Coiflets wavelet family of order 4 ('coif4')
4**□0*	1	S_6 approximation level
	2	S_7 approximation level
	3	S_8 approximation level
4***0□	1	exponential decay to the median with the decay parameter $\lambda = \frac{1}{30}$
	2	exponential decay to the median with the decay parameter $\lambda = \frac{1}{180}$

Note: The six digit codes of the 129 models tested in this study. A star (*) indicates that a certain digit can take one of a few values and is used to represent subgroups of models. A square cup ('□') identifies the digit of interest. Note that for consistency with a recent study [21], the first digit of the wavelet-based model family is a '4', not a '3'.

III. MODELS AND THEIR CODES

To cope with the abundance of results – we consider 129 distinct LTSC models in this study – all models are given a unique 6-digit code for identification, see Table I. The first digit defines the model family, the second represents the length of the calibration window (in years – 2, 3 or 4). The remaining four digits define family-specific characteristics. A star (*) indicates that a certain digit can take one of a few values and is used to represent subgroups of models.

A. Simple linear and exponential models (1*000*)

This family is essentially composed of simple models used as a benchmark for the more elaborate techniques described in the following sections. We initially considered the following three models:

- the mean of the spot price in the calibration window (models **1*0001**),
- linear regression of the spot price in the calibration window extrapolated into the forecasting window (models **1*0002**) and
- the median of the spot price in the calibration window (models **1*0003**).

But later, based on their poor forecasting performance in the short- and mid-term (up to half a year) and a surprisingly good performance of the median models (**1*0003**) in the long-term (over half a year), we decided to enlarge the family to include two models with an exponential decay from the current spot price (x_0) to the median (x_T):

$$f_{exp}(x) = (x_0 - x_T) \times \frac{e^{-\lambda x} - e^{-\lambda x_T}}{1 - e^{-\lambda x_T}} + x_T, \quad (1)$$

where x_0 is the last observation in the calibration window (i.e., on the day the prediction is made), x_T is the median of the spot prices in the calibration window (on the last day of the forecast window) and $\lambda = \frac{1}{30}$ (models **1*0004**) or $\frac{1}{180}$ (models **1*0005**). Since $e^{-\lambda x}$ is the tail of the exponential distribution with mean $\frac{1}{\lambda}$, the forecast of models **1*0004** decays to the median much faster than of **1*0005**. Finally, we extended the family to include two dummy-based methods:

- monthly dummies with the values computed as mean spot price in a given calendar month (models **1*0007**) and
- monthly dummies with the values computed as median spot price in a given calendar month (models **1*0008**).

B. Sine-based models (2***00)

The second analyzed family of models is based on the Fourier decomposition of the original signal. Using nonlinear least squares we fit a sum of one up to four sines to the spot price P_t in the calibration window. The third digit in the model code (**2*□*00**) stands for the number of sines used. Each sine function has three parameters to estimate – amplitude, period and phase shift. To find an answer to the question whether the periods of the sine functions of higher frequency should be harmonics of the annual frequency, we examine three subgroups of models:

- models where the periods of all sines (up to four) are estimated within the least squares procedure (models **2**100**, i.e., with '1' as the fourth digit),
- models where the period of the first sine function is estimated within the least squares procedure and the periods of the remaining sine functions (if any) are set to a year, half a year and a third of a year (models **2**200**, i.e., with '2' as the fourth digit) and
- models where the periods are set to a year, half a year, a third of a year and a quarter of a year (models **2**300**, i.e., with '3' as the fourth digit).

Note that forecasting any of the sine-based LTSCs is straightforward. A sum of sines is simply extrapolated into the future.

C. Wavelet-based models (4***0*)

The third family comprises wavelet-based models. Note that for consistency with a recent study [21], the first digit of the family code is a '4', not a '3'. To obtain a smoothed signal, i.e., the LTSC of electricity spot prices, we apply the Discrete Wavelet Transform (DWT). Recall, that any function or signal (here, P_t) can be built up as a sequence of projections onto one father wavelet and a sequence of mother wavelets: $S_J + D_J + \dots + D_1$, where 2^J is the maximum scale sustainable by the number of observations [12, 22]. At the coarsest scale the

signal can be estimated by S_J . By adding a mother wavelet D_j of a lower scale $j = J, J-1, \dots$ we obtain a better estimate of the original signal, e.g. $S_{J-1} = S_J + D_J$. In this study we use $J = 6, 7$ and 8 , which roughly correspond to bimonthly ($2^6 = 64$ days), seasonal ($2^7 = 128$ days) and annual ($2^8 = 256$ days) smoothing, respectively.

A characteristic feature of wavelets is that – unlike sines and cosines – the individual wavelet functions are localized in time and converge to zero for large (positive or negative) arguments; the different families and orders of wavelets make different trade-offs between how compactly they are localized in time and their smoothness. In the context of forecasting this means that some additional assumptions have to be made on how to extrapolate the smoothed signal. There have been a few suggestions in the literature on how to deal with this problem. For instance, [32] used a spline fit while [31] applied polynomial extrapolation. Unfortunately, the spline- or polynomial extrapolation-based forecasts of electricity spot prices behave unpredictably over periods of a few hundred days. Stevenson *et al.* [24, 25] considered predictions of threshold autoregressive models (TAR) fitted to wavelet-smoothed spot prices. In these two papers wavelets were used to forecast electricity prices for horizons of more than a few days ahead. However, prices from the out-of-sample period were used to extend the signal to the nearest power of two and avoid edge extension problems. Hence, the predictions were not truly *ex-ante* forecasts.

Since we are interested in *ex-ante* forecasts with a relatively long time horizon we had to come up with a different method. Motivated by the surprisingly good long-term forecasts of the simple models (recall the discussion in Section III-A) and the potential of wavelets yield good short-term forecasts we introduced a family of wavelet-based models an exponential decay to the median ($4^{***}0^*$). In these models the calibration windows are first extended one year forward using an exponentially decaying to the median deterministic function. This is done analogously as in models 1^*0004 and 1^*0005 : we connect the last day of the calibration period (on the time axis) and the current spot price (on the price axis) with the last day of the forecast window (on the time axis) and the median of the spot prices in the calibration window (on the price axis).

Once the data series are extended to 1095, 1460 or 1825 (depending on the length of calibration window) observations we apply the DWT. The wavelet estimation procedure operates only on vectors with length of a power of two. Otherwise the series is artificially extended before applying DWT. In the wavelet family of models ($4^{***}0^*$) a constant extension at the edges is used. Note that does not influence the shape of the wavelet smoother too much since the last observation of the initially extended series (of 1095, 1460 or 1825 observations) is the median. Finally, we simply take as our forecast the 365 values of the obtained wavelet smoother corresponding to the forecast window.

We use four types of wavelets:

- two from the Daubechies family (of order 12 – $4^*1^*0^*$ and 24 – $4^*2^*0^*$; in Matlab and later in the text denoted by ‘db12’ and ‘db24’, respectively) and
- two from the Coiflets family (of order 2 – $4^*3^*0^*$ and 4

– $4^*4^*0^*$; denoted by ‘coif2’ and ‘coif4’, respectively).

The fourth digit in the model code defines the wavelet approximation level: S_6 ($4^{**}10^*$), S_7 ($4^{**}20^*$) and S_8 ($4^{**}30^*$), see Table I.

IV. THE EMPIRICAL STUDY

A. EEX and Nord Pool spot price data

In this study we concentrate on two major European power markets: the European Energy Exchange (EEX; Germany) and the Nord Pool market (NP; Scandinavia). We use mean daily (baseload) spot prices from the period Jan 1, 2001 – Apr 12, 2011 (3754 obs.) for EEX and from the period Jan 1, 2000 – Nov 13, 2008 (3240 obs.) for Nord Pool, see Figure 1. Note that the annual seasonality is generally irregular, if visible at all. The more regular weekly periodicity cannot be seen too well at this time scale. However, if we increase the resolution – as in Figures 2 and 3 – the five weekdays vs. weekend pattern becomes apparent.

B. The rolling window scheme

At each estimation/forecasting step we move forward the starting and the ending date of the calibration sample by one day. Every model, out of the 129 analyzed, is estimated on three *calibration windows*: a two-year (730-day), a three-year (1095-day) and a four-year (1460-day). The following year (365 days), denoted in the article as the *forecast window*, is used for the out-of-sample forecast, see Figures 2 and 3. In order to obtain exactly the same number of forecasts for all three calibration windows, the one-year window has a 730-day lag (i.e., starts from the 731st observation) and the two-year has a 365-day lag. The rolling procedure continues as long as we have at least 365 observations following the last day of the calibration window. In this way we obtain 1930 forecasts (each from 1 to 365 days ahead) for the German EEX market and 1416 for the Scandinavian Nord Pool.

C. Error measures

Having computed all the forecasts, we calculate three measures of forecast accuracy – the mean absolute error (MAE), the mean squared error (MSE) and the mean absolute percentage error (MAPE) – for each dataset, each model and each of the six forecast horizons. Then we rank the models from 1 to 129 based on the values of $MAE_{h,d}$ or $MSE_{h,d}$:

- separately for each of the six forecast horizons: $h = 1$ (1-7 days), 2 (8-30 days), 3 (31-90 days), 4 (91-182 days), 5 (183-274 days) and 6 (275-365 days) and
- each of the datasets $d = 1$ (EEX), 2 (NP).

To obtain the aggregate rank over both datasets of a model for a given time horizon h we calculate the geometric mean, denoted by $GM(MAE_{h,*})$ or $GM(MSE_{h,*})$, of the two ranks for each of the six datasets for this time horizon. Next, we compute an average rank over all time horizons: again we rank the models from 1 to 129 based on the values of $GM(MAE_{h,*})$ or $GM(MSE_{h,*})$ for each of the six time horizons and compute the geometric mean of those six ranks. The

Fig. 1. Mean daily (baseload) electricity spot prices from two power markets European Energy Exchange (EEX, Germany) and Nord Pool (NP, Scandinavia).

resulting two global measures are denoted by $GM(MAE_{*,*})$ and $GM(MSE_{*,*})$, see Table II.

Since the ranks do not provide quantitative information about a given method's forecasting accuracy we use two aggregate measures based on the individual mean absolute percentage errors ($MAPE_{h,d}$ with $h = 1, \dots, 6$, $d = 1, 2$). Namely, for a given time horizon h we calculate the weighted arithmetic mean

$$MAPE_{h,*} = \sum_{d=1}^2 w_d \cdot MAPE_{h,d}, \quad (2)$$

where $w = (\frac{1930}{3346}, \frac{1416}{3346})$ represents weights for both datasets (weights are proportional to lengths of the datasets). Next, we compute the average over all time horizons:

$$MAPE_{*,*} = \sum_{h=1}^6 v_h \cdot MAPE_{h,*}, \quad (3)$$

where $v = (\frac{7}{365}, \frac{23}{365}, \frac{60}{365}, \frac{92}{365}, \frac{92}{365}, \frac{91}{365})$ is the vector of weights such that each forecasting horizon has a weight proportional to its length. For a given model the global error measure $MAPE_{*,*}$ is the mean absolute percentage error over all datasets and all forecasting horizons, see Table II.

V. RESULTS

In Table II we list the top 10 models according to each of the three global forecast error measures: $GM(MAE_{*,*})$,

TABLE II
TOP 10 MODELS ACCORDING TO EACH OF THE THREE GLOBAL FORECAST ERROR MEASURES

No.	$GM(MAE_{*,*})$	Model	$GM(MSE_{*,*})$	Model	$MAPE_{*,*}$	Model
1	9.94	432301	9.55	432302	28.8%	432301
2	10.17	431302	11.03	431302	28.82%	431301
3	10.66	431301	11.03	422302	28.99%	434301
4	14.72	431102	11.94	434302	29.29%	433301
5	15.06	432302	12.62	424302	29.40%	433201
6	15.19	432102	14.86	423102	29.45%	434201
7	15.22	431202	15.66	434102	29.48%	431201
8	17.66	434102	16.23	423302	29.51%	432201
9	18.34	130005	16.75	423301	29.55%	433101
10	18.74	434301	16.82	431301	29.58%	434101
...	...	...	...	...	...	...
12	...	...	...	...	29.62%	130004
20	...	...	20.53	130001	...	...
28	...	...	27.64	234200	...	...
31	27.98	232200	...	...	...	...
81	...	...	...	...	33.43%	231100

Note: The best three models in terms of each measure are emphasized in bold. Some models, like 432302, is in the top three for one measure ($GM(MSE_{*,*})$) and in the top 10 for another measure ($GM(MAE_{*,*})$). Note that all models in the top 10 list are from families 4***0* except one from family 1*000* (i.e., 130005); the best models from the remaining families are listed in the bottom rows of the table. See Section III for model codes and Section IV-C for error measure definitions.

Fig. 2. Sample LTSC estimation and forecasting results for the EEX market and a three-year calibration window Jul 9, 2005 – Jul 7, 2009. Clearly the dummy and sinusoidal LTSCs (*top panel*) do not follow the trend-seasonal pattern of the spot prices in the calibration window as well as the wavelet LTSCs (*bottom panel*). For code definitions see Table I).

$GM(MSE_{*,*})$ and $MAPE_{*,*}$. Almost all of the top models (29 out of 30) come from family 4***0* estimated using either a two- or a three-year calibration window, with a strong dominance of latter (i.e., 43***0*). Models from the other two families are on much lower positions. The best models from families 1*000* and 2***00 are on positions 9 and 31 for $GM(MAE_{*,*})$, 20 and 28 for $GM(MSE_{*,*})$ and 12 and 81 for $MAPE_{*,*}$, respectively. Only one of the simple models (i.e., 130005 – the median spot price in the calibration window as the forecast) makes it to the top 10, but only according to $GM(MAE_{*,*})$.

In the set composed of the three top models according to each of the three global measures; emphasized in bold in Table II) all but one come from subfamily 43*30*, i.e. wavelet-based with the S_8 approximation level and calibrated on a three-year window. Furthermore, model 432301 is the best according to $GM(MAE_{*,*})$ and $MAPE_{*,*}$, but is not in the top 10 according to $GM(MSE_{*,*})$. On the other hand, model 431302 is the second best according to $GM(MAE_{*,*})$ and $GM(MSE_{*,*})$, but is not in the top 10 according to $MAPE_{*,*}$. Generally, $MAPE_{*,*}$ prefers wavelet-based models with a faster decay in the forecasting window ($\lambda = \frac{1}{30}$, models 4***01), while $GM(MSE_{*,*})$ models with a slower decay ($\lambda = \frac{1}{180}$, models 4***02). Unfortunately, it's hard to choose the optimal wavelet family based on these results.

The above observations are confirmed if we look at the performance across the forecasting horizons. In Figure 4 we

plot histograms depicting how many times models from a given family are ranked in the top 5 (ca. 4%), top 10 (ca. 8%) and top 25 (ca. 20%) of all 129 models according to $GM(MAE_{h,*})$, $GM(MSE_{h,*})$ and $MAPE_{h,*}$, for $h = 1, \dots, 6$. We can clearly see that models from family 4***0* dominate the rankings in terms of all three error measures. Within this family the three-year calibration window (43***0*) is uniformly better than the two- and four-year windows. We can conclude that extending the calibration window up to four years does not improve the forecasting results. Moreover, for families 1*000* and 2***00 also the three-year window leads to the best results, see Table II and Figure 4.

Finally, note that models which use monthly dummies (1*0007 and 1*0008) are far behind the wavelet-based approaches. Nearly all of them are ranked in the second half of the global rankings: between 74 and 126 for $GM(MAE_{*,*})$, between 91 and 125 for $GM(MSE_{*,*})$, and between 78 and 122 for $MAPE_{*,*}$.

VI. CONCLUSIONS

In this paper we have presented the results of an extensive empirical study in an attempt to find the best model (technique) for estimating and ultimately forecasting the long-term seasonal component (LTSC) of electricity spot prices. We have considered a vast array of models from three families:

- 21 simple linear and exponential models, including monthly dummies (denoted in the text by 1*000*),

Fig. 3. Sample LTSC estimation and forecasting results for the Nord Pool market and a two-year calibration window Nov 30, 2001 – Nov 28, 2004. The sinusoidal LTSCs (*top panel*) do not follow the trend-seasonal pattern even if the periods – as well as the amplitudes and phases – of four sine waves are estimated within an optimization procedure (model 234100). For code definitions see Table I.

- 36 sine-based models, being sums of up to four sines of different periods, amplitudes and phase shifts ($2^{***}00$), and
- 72 wavelet-based models, with the wavelet smoother (S_6 , S_7 or S_8) calibrated to a signal extrapolated using a function exponentially decaying to the median of the spot price in the calibration window ($4^{***}0^*$).

Although we have tested the models only in two markets (the German EEX and the Scandinavian Nord Pool), most likely the conclusions will be similar for other datasets.

The outcomes of our study clearly question the validity of using monthly dummies and sine functions to model the LTSC. Essentially all wavelet-based models provide not only a better out-of-sample prediction of future electricity spot prices but also a much better in-sample fit.

In this empirical exercise, subfamily $43^{*}30^{*}$ yielded the best forecasts. However, this might not be the overall best performing model. In particular, in view of a recent empirical study [16], which showed that improved robustness of the electricity spot price model could be achieved by filtering the data with some reasonable procedure for outlier (i.e., spike) detection, and then using classical estimation techniques for the seasonal pattern on the filtered data. While no single best method for outlier detection could be identified, in a vast majority of cases all of the considered filtering techniques significantly outperformed the no filter' approach that used the original spot price (and that we use here), for details see

[16]. This idea definitely deserves a thorough investigation and to some extent has been analyzed in a recent study [21].

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Fig. 4. Histograms showing how many times models from a given family (1*000*, 2***00, 4***0* are ranked in the top 5 (top row), top 10 (center row) and top 25 (bottom row) of all 129 models according to GM(MAE_{*h,**}) and GM(MSE_{*h,**}), for $h = 1, \dots, 6$ (in columns, from left to right). Clearly models from family 43**0* dominate the rankings.

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