

Robust estimation and forecasting of the long-term seasonal component (LTSC) of electricity spot prices*

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Introduction

- When building electricity spot price models we should address two questions:
 - How to estimate the trend-seasonal component?
 - How to forecast it?



3 approaches to LTSC modeling

1 Piecewise constant functions or dummies

- Non-smooth LTSC with jumps between months

Bhanot (2000), Fanone et al. (2012), Fleten et al. (2011), Gianfreda and Grossi (2012), Haldrup et al. (2010), Haugom and Ullrich (2012), Higgs and Worthington (2008), Knittel and Roberts (2005), Lucia and Schwartz (2002)

2 Sinusoidal functions (also coupled with EWMA)

- Annual periodicity can hardly be observed in market data

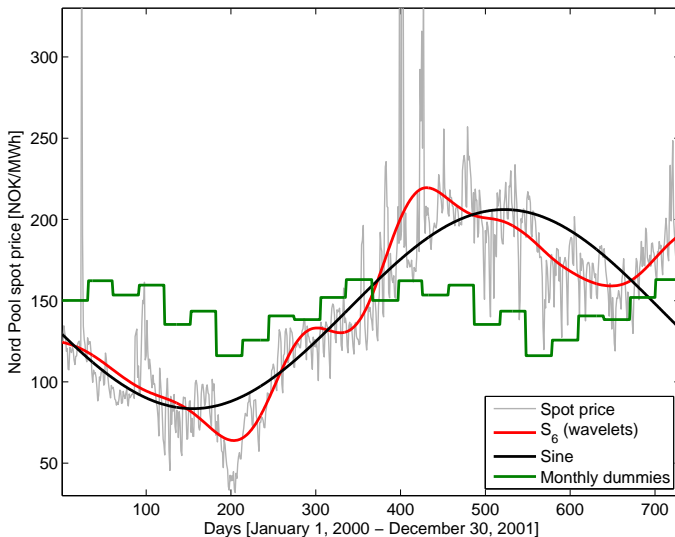
Benth et al. (2012), Bierbrauer et al. (2007), Cartea and Figueroa (2005), De Jong (2006), Geman and Roncoroni (2006), Janczura et al. (2013), Lucia and Schwartz (2002), Pilipovic (1998), Weron (2008)

3 Wavelets or other nonparametric smoothers

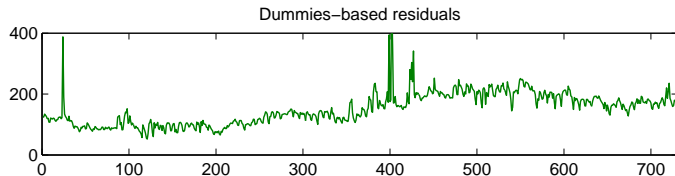
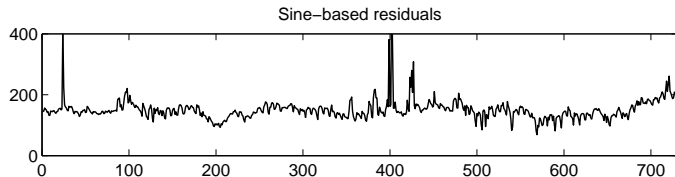
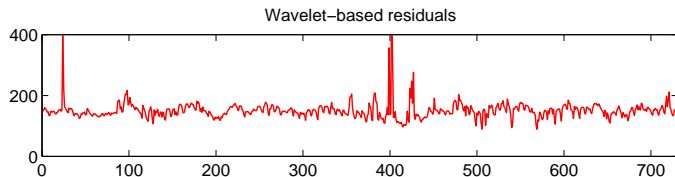
- More robust to outliers and less periodic
- ... but forecasting of a nonparametric LTSC is not trivial

Bordignon et al. (2013), Conejo et al. (2005), Janczura et al. (2013), Janczura and Weron (2010,2012), Stevenson (2001), Schlueter (2010), Stevenson et al. (2006), Weron (2006,2009), Weron et al. (2004)

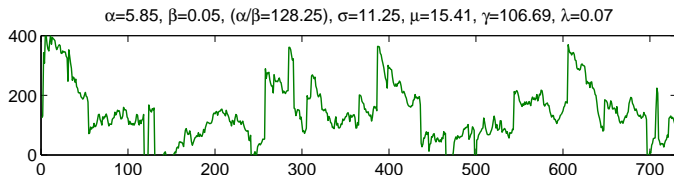
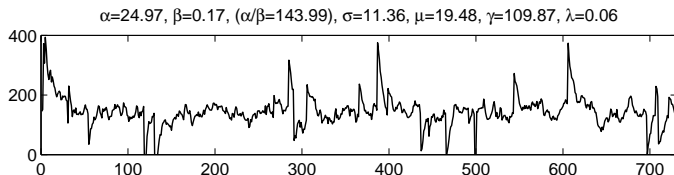
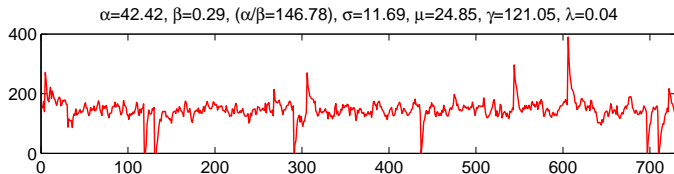
3 LTSC fits to Nord Pool spot prices



3 stochastic components (residuals)



3 MRJD fits: $dX = (\alpha - \beta X)dt + \sigma dB + \mathcal{N}(\mu, \gamma)dN(\lambda)$



Conclusions ... so far

- In-sample the wavelet-based LTSC (**red**) is clearly the best
 - This is not a surprise, given the more degrees of freedom the nonparametric models have
- But how does the wavelet-based LTSC perform out-of-sample?
- How to forecast it?

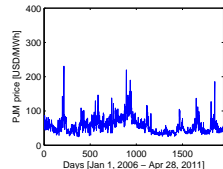
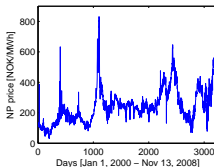
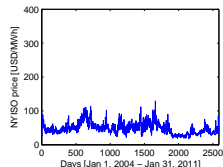
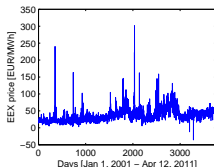
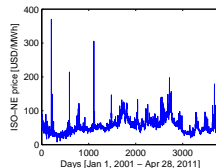
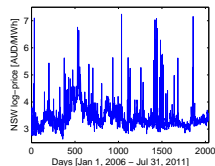


- Introduction
- **Datasets and models**
- Estimating and forecasting the LTSC
- Results
- Conclusions

Daily electricity spot prices

6 markets:

- NSW, Australia (2038 obs.)
- EEX, Germany (3754 obs.)
- Nord Pool, Scandinavia (3240 obs.)
- ISO-NE, U.S. (3770 obs.)
- NYISO, U.S. (2588 obs.)
- PJM, U.S. (1944 obs.)



304 models: Simple and sine-based models

- Simple models (**1*000***) → 16 models
 - mean, median, linear regression
 - linear/exponential decay from the current spot price to the median
 - dummies: mean-based, median-based
- Sines fitted to raw prices (**2***00**) → 24 models
 - 1-4 sines used
 - periods estimated or set to 1, $\frac{1}{2}$, $\frac{1}{3}$ and $\frac{1}{4}$ of a year
- Sines fitted to spike-filtered prices (**3****0**) → 48 models
 - Spikes replaced by the mean or the upper/lower 2.5% quantiles of the deseasonalized prices

304 models: Wavelet-based models

- Wavelets with an exponential decay to the median fitted to raw prices (**4***0***) → 48 models
 - 4 types of wavelets (Daubechies, Coiflets)
 - 3 approximation levels (6, 7, 8)
 - 2 exponential decay constants
- Wavelets with a linear decay to the median fitted to raw prices (**5***00**) → 24 models
- Wavelets with an exponential decay to the median fitted to spike-filtered prices (**6*******) → 96 models
 - Spikes replaced by the mean or the upper/lower 2.5% quantiles of the deseasonalized prices
- Wavelets with an exponential decay to the median fitted to spike-filtered prices (**7****0**) → 48 models

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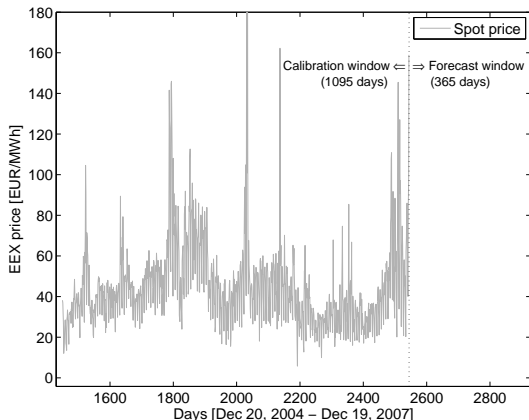
Estimation and forecasting scheme

2 calibration windows
(rolling windows):

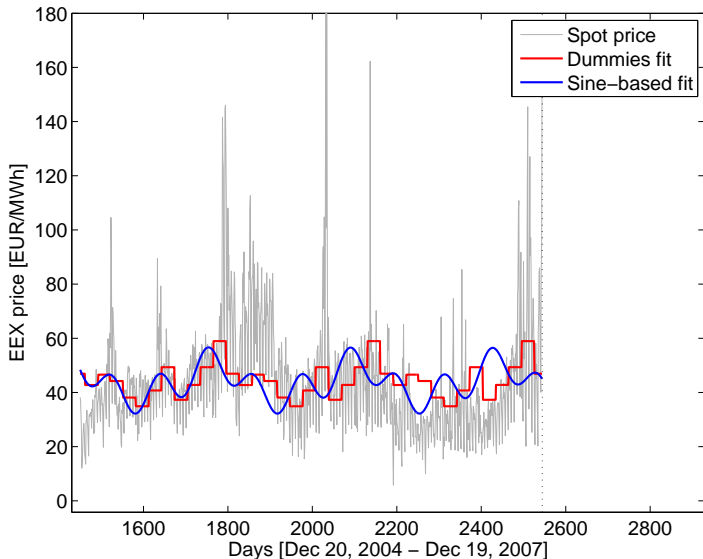
- 2-year (730 days)
- 3-year (1095 days)

6 forecast horizons:

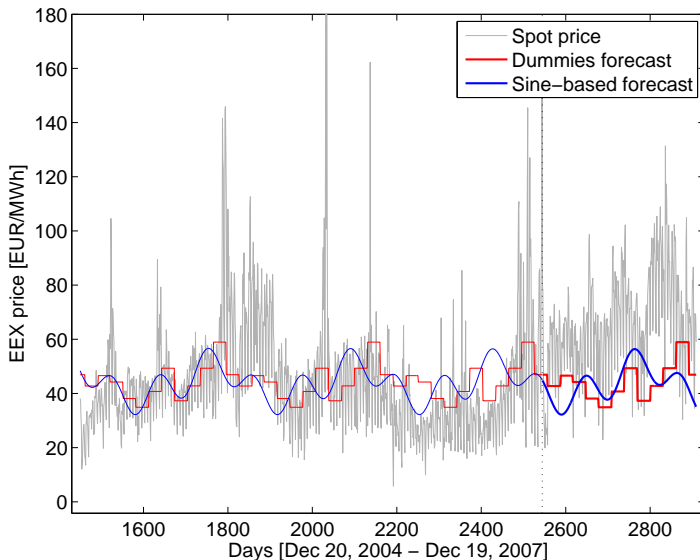
- 1-7 day, 8-30, 31-90
- 91-182 (2nd Qtr)
- 183-274 (3rd Qtr)
- 275-365 (4th Qtr)



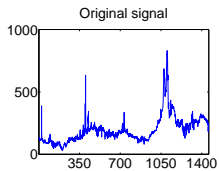
Estimation: Dummies and sines



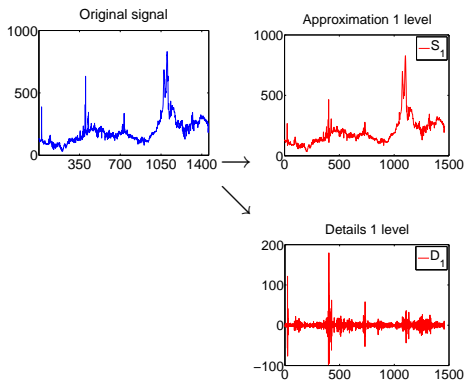
Forecasting: Dummies and sines



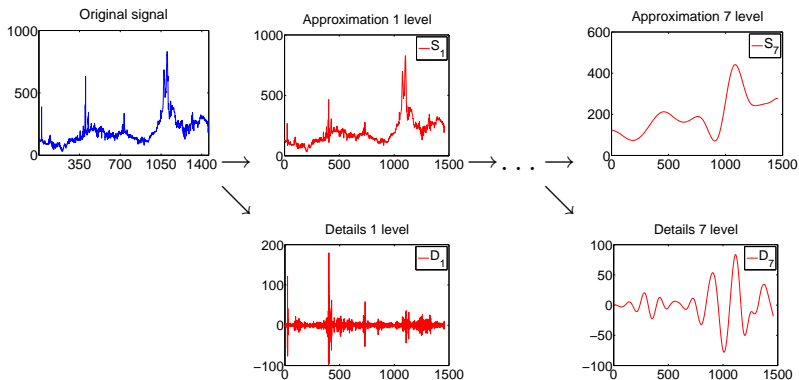
Decomposition of a signal



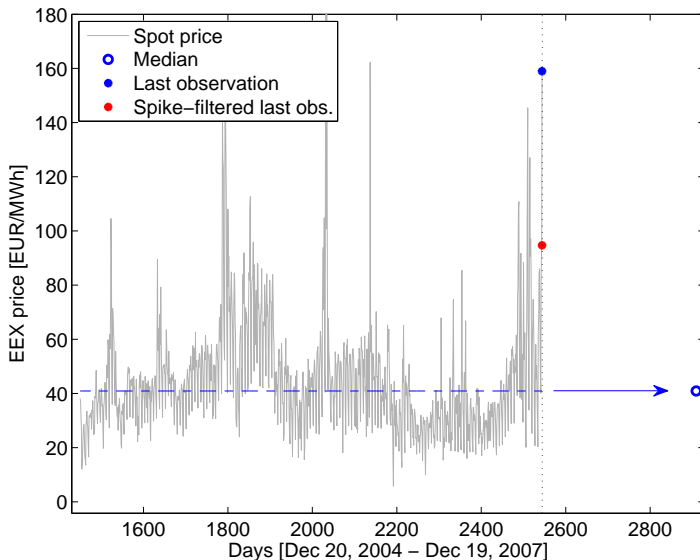
Decomposition of a signal



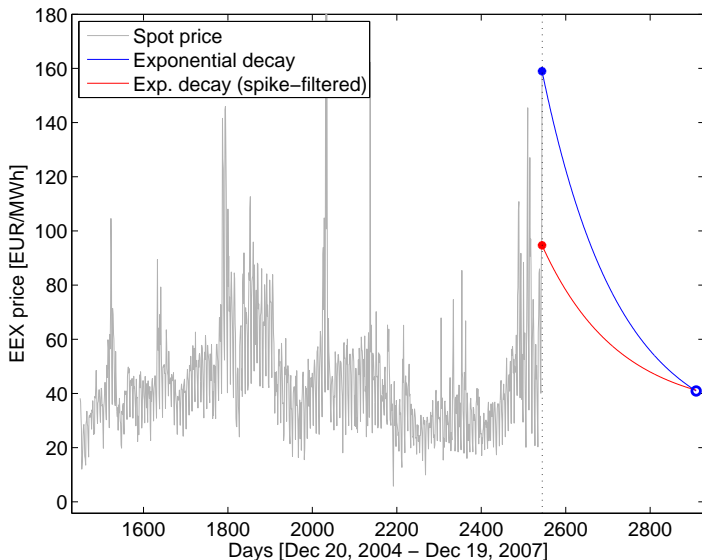
Decomposition of a signal



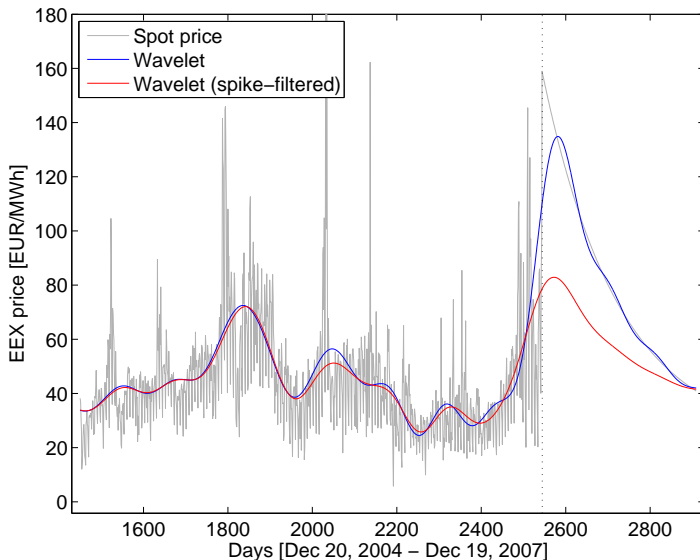
Estimation and forecasting: Wavelets



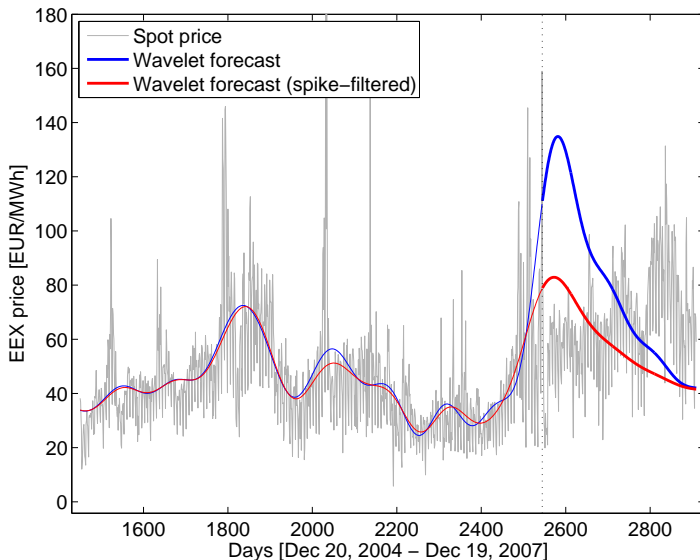
Estimation and forecasting: Wavelets cont.



Estimation and forecasting: Wavelets cont.



Estimation and forecasting: Wavelets cont.



Agenda

- Introduction
- Datasets and models
- Estimating and forecasting the LTSC
- **Results**
- Conclusions

Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
d_1						
d_2						
d_3						
d_4						
d_5						
d_6						

- For every dataset d_i and every forecasting horizon h_j we **rank** the models according to MAE, MSE and MAPE

Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
d_1						
d_2						
d_3						
d_4						
d_5						
d_6						

- For every dataset d_i and every forecasting horizon h_j we **rank** the models according to MAE, MSE and MAPE
 - For each dataset we calculate the geometric means $GM(MAE_{*,d})$ and $GM(MSE_{*,d})$ of the ranks

Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
d_1						
d_2						
d_1						
d_2						
d_1						
d_2						

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 - For each dataset we calculate the geometric means $GM(MAE_{*,d})$ and $GM(MSE_{*,d})$ of the ranks
 - For each horizon we calculate the geometric means $GM(MAE_{h,*})$ and $GM(MSE_{h,*})$ of the ranks

Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
d_1						
d_2						
d_1						
d_2						
d_1						
d_2						

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 - For each horizon we calculate the geometric means $GM(MAE_{h,*})$ and $GM(MSE_{h,*})$ of the ranks
 - We also calculate the **global** geometric means $GM(MAE_{*,*})$ and $GM(MSE_{*,*})$ of the ranks

Evaluating forecasting performance

	h_1	h_2	h_3	h_4	h_5	h_6
d_1						
d_2						
d_1						
d_2						
d_1						
d_2						

- For every dataset d_i and every forecasting horizon h_j we **rank** the models according to MAE, MSE and MAPE
 - For each dataset we calculate the geometric means $GM(MAE_{*,d})$ and $GM(MSE_{*,d})$ of the ranks
 - For each horizon we calculate the geometric means $GM(MAE_{h,*})$ and $GM(MSE_{h,*})$ of the ranks
 - We also calculate the **global** geometric means $GM(MAE_{*,*})$ and $GM(MSE_{*,*})$ of the ranks
- Finally, we calculate $MAPE_{*,d}$, $MAPE_{h,*}$ and the **global** $MAPE_{*,*}$

Results

Top 15 models according to each of the three global forecast error measures

No.	GM(MAE _{*,*})	Model	GM(MSE _{*,*})	Model	MAPE _{*,*}	Model
1	17.13	731310	10.84	623322	30.04%	734110
2	23.37	723310	13.75	622322	30.04%	732110
3	23.93	631312	14.71	624322	30.06%	733110
4	24.86	623322	20.98	631322	30.06%	723310
5	24.86	722110	24.82	631312	30.08%	731110
6	25.16	723320	24.91	633122	30.09%	724310
7	25.58	721110	25.63	624122	30.14%	731310
8	25.91	724310	25.82	621322	30.15%	623322
9	26.44	623312	28.87	634122	30.16%	624322
10	26.97	724110	29.50	621122	30.18%	722310
11	29.49	623122	29.74	722320	30.20%	724320
12	29.82	722310	30.76	721120	30.20%	721110
13	29.94	624322	31.96	623122	30.20%	722110
14	30.97	624122	32.77	422302	30.21%	723320
15	31.25	723110	32.88	424302	30.26%	722320

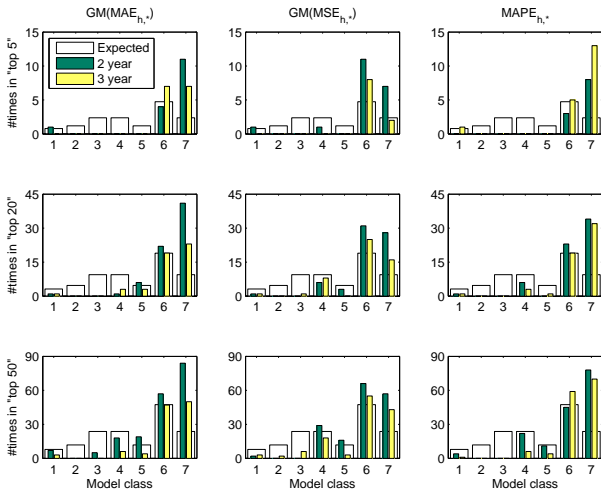
Results cont.

... models according to each of the three global forecast error measures

No.	GM(MAE _{*,*})	Model	GM(MSE _{*,*})	Model	MAPE _{*,*}	Model
51	30.51%	423302
55	53.42	523300
69	.	.	71.88	130001	.	.
70	62.27	423302
79	.	.	77.29	524200	.	.
82	70.87	120005
105	30.91%	524300
120	31.14%	130005
128	98.93	120008
173	.	.	143.57	231100	.	.
174	.	.	143.72	331110	.	.
182	.	.	148.64	130008	.	.
209	192.24	324320
225	34.47%	130008
226	206.55	232200
228	36.91%	331110
241	37.43%	231300

Results cont.

The number of times models from a given family are ranked in the top 5, 20 and 50 of all 304 models according to $GM(MAE_{h,*})$, $GM(MSE_{h,*})$ and $MAPE_{h,*}$ for each of the six forecast horizons $h = 1, \dots, 6$



Conclusions

- A comprehensive study on the forecasting of the LTSC
- Over 300 models examined, including commonly used and new approaches
- Wavelet-based models outperform sine-based and monthly dummy models
 - Both in-sample (modeling) and out-of-sample (forecasting)
- Validity of stochastic models built on sines or monthly dummies is questionable