A Stability Analysis of the Nord Pool System using Hourly Spot Price Data

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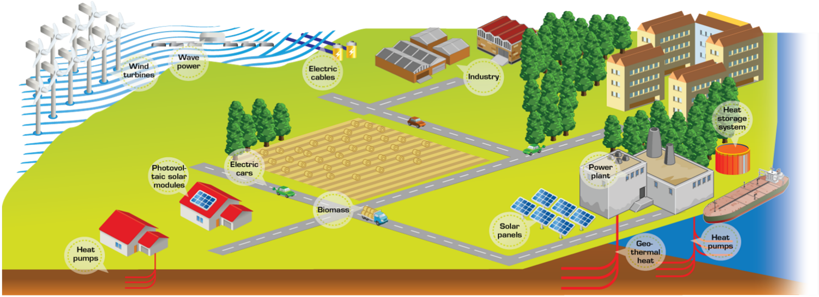
LUND UNIVERSITY

Overview

Stability analysis

The power system is a complex connected system.



Stability analysis: Simplifications

Google Flu Trends uses aggregated Google search data to estimate current flu activity around the world in near real-time.

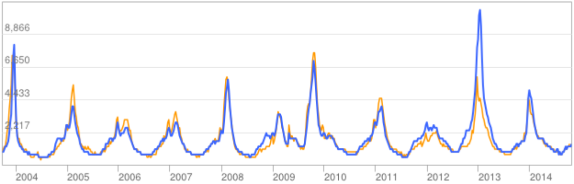


Figure: United States: Influenza-like illness (ILI) data provided publicly by the U.S. Centers for Disease Control. Blue line Google Flu, orange line is reported cases

Their method is published in Nature **457**, 1012-1014 (19 February 2009) | doi:10.1038/nature07634

Idea: Mimic Google Flu

Prices on the electricity spot and futures are available on the Nord Pool web site. Could we use these data?

- Prediction markets (bet money on your opinion) outperformed election polls in nearly every US presidential election between 1988-2004 (Berg et al. [2008])
- Google "knew" from search data who would win the US presidential election (Guessed right in nearly every state)
- Google search data also predicted that Donald Trump would win the 2016 election!
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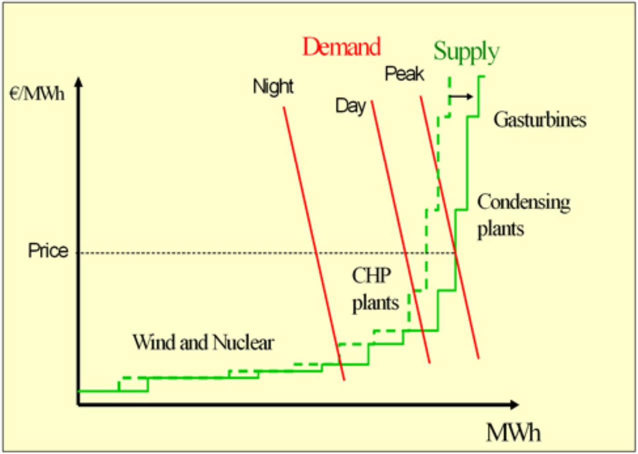
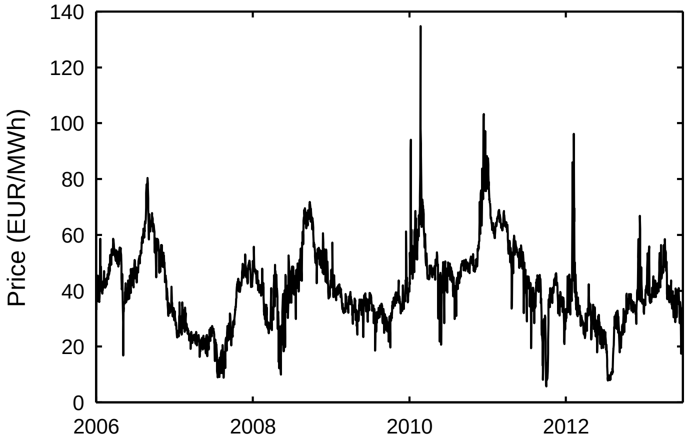
The electricity market

The electricity price is given by the equilibrium between supply and (the inelastic) demand. High prices are cause by lack of supply.



Electricity spot price

The spot price is the price for one or 24 hours ahead (Nord Pool).



Stylized facts

It is generally agreed upon that the spot price is

- Mean reverting
- Seasonal (yearly, weekly, daily)
- Heteroscedastic (the conditional variance is not constant)
- There are spikes and drops (jumps)

Also, it is clear the (by studying forward prices) that the spot price is not Markovian.

Heuristic model design, focus on extreme events

There are essentially three distinct modes in the market

- Excess demand $\Rightarrow$ High prices
- Normal conditions $\Rightarrow$ the spot price varies around some normal level
- Excess supply (typically due to renewables) $\Rightarrow$ very low or even negative prices.

This observation suggests that a Hidden Markov Model is appropriate!

Question: What is a normal level?

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Independent Spike Models

A company trading in electricity will typically

- Use forward contracts to cover their obligations in the future and
- Use the spot market to make up the difference between their position in forwards and the actual position.

The spread between these is therefore of interest. This is the focus of the *Independent Spike Models*

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Forward prices

A forward contract[1] is valued according to

$$F_n = p(t_n, t_n + T)\mathbb{E}^{\mathbb{Q}}\left[\frac{1}{T}\int_{t_n}^{t_n+T} s(u)\mathrm{d}u|\mathcal{F}(t_n)\right]. \qquad (1)$$

Here $s(\cdot)$ is the electricity spot price and $p(t_n, t_n + T)$ is a zero coupon bond with maturity T and $\mathbb{Q}$ is some (non-unique) equivalent risk neutral probability measure.

[1] The contract is a swap contract, but is often called a forward contract

Independent Spike Models

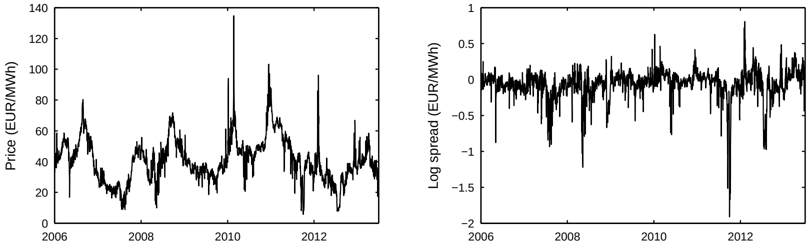


Figure: Nord Pool Spot and spread

Independent Spike Models

The logarithm of the electricity spot price $y_n = \log(s_n)$ is modeled as an autoregressive model with heteroscedastic noise in the base regime (reverting to the logarithm of the one-month ahead forward price adjusted for the risk premium), while the spikes and drops are modeled as *iid* random variables.

$$y_{n+1} = \begin{cases} y_n + a(\mu_n - y_n) + \sigma y_n^{\gamma} z_n & \text{if } R_{n+1} = B \\ f_n + \xi^S & \text{if } R_{n+1} = S \\ f_n - \xi^D & \text{if } R_{n+1} = D \end{cases} \tag{2}$$

where the mean reversion level $\mu_n = \eta \log(F_n)$ is a factor compensating for the risk premium η times the logarithm of the month ahead forward

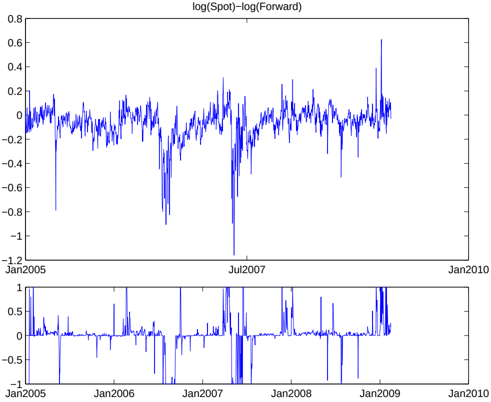
Independent Spike Models

The switching between regimes is governed by a Markov chain $\{R\}$ having a transition matrix

$$P = \begin{pmatrix} 1 - p_{BS} - p_{BD} & p_{BS} & p_{BD} \\ p_{SB} & 1 - p_{SB} & 0 \\ 1 - p_{DB} & 0 & p_{DB} \end{pmatrix} \quad (3)$$

The model does not allow for transitions directly from spikes S to drops B, as these transitions are very unlikely in the real world; including them in the model would add complexity without any real gains.

Fit to EEX market data



Note that spikes and drops do not occur randomly in time!

Make the transition matrix time invariant

The transition matrix is given by

$$P(Z_t) = \begin{pmatrix} 1 - p_{BS}(Z_t) - p_{BD}(Z_t) & p_{BS}(Z_t) & p_{BD}(Z_t) \\ p_{SB}(Z_t) & 1 - p_{SB}(Z_t) & 0 \\ 1 - p_{DB}(Z_t) & 0 & p_{DB}(Z_t) \end{pmatrix} \tag{4}$$

The transition probabilities in the Markov chain is modeled as

$$p_{BS}(Z_t) = \frac{\exp\left(\beta_{BS,0} + \beta_{BS,1} Z_t\right)}{1 + \exp\left(\beta_{BS,0} + \beta_{BS,1} Z_t\right) + \exp\left(\beta_{BD,0} + \beta_{BD,1} Z_t\right)} \tag{5}$$

Consumptions and/or production is a good variable, all parameters are significant! Reserve margin did not perform as well, nor did wind power production.

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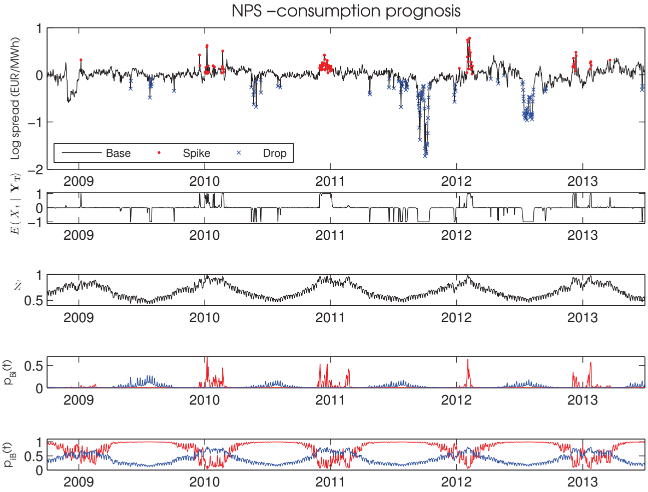
Applied to the Nord Pool market



Interpretation

The model provides an estimates of the probability to spike, to drop and/or revert from any of these.

- Only using public information
- Difficult to manipulate the data

What if we did?

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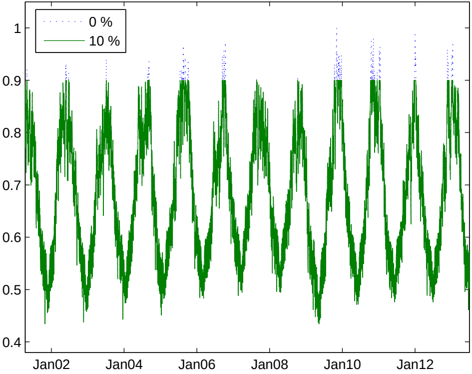
What if we did?

What if we modified the consumption

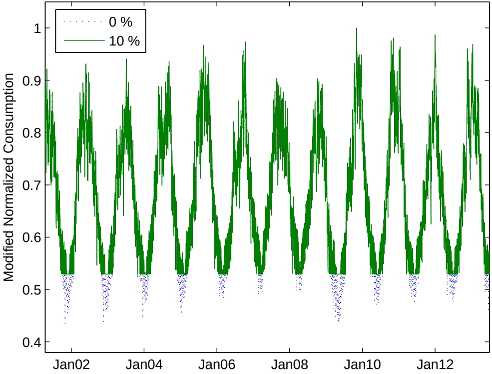
- By capping large consumption?
- By increasing minimum consumption
- Doing both (i.e. having a super-duper battery)
- Or adding more renewables

Capping



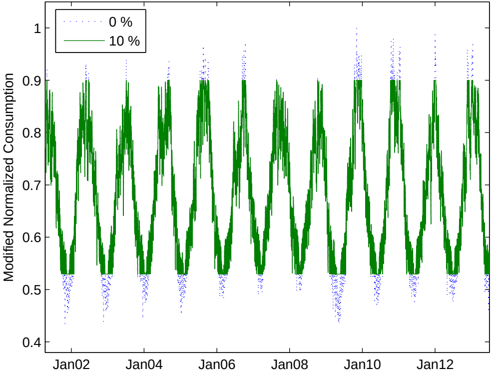
Battery capacity (%)	0	5	10	15	20
Base prob.	0.8794	0.8806	0.8902	0.9016	0.9072
Spike prob.	0.0304	0.0292	0.0196	0.0081	0.0025
Drop prob.	0.0902	0.0902	0.0902	0.0902	0.0904

Increasing lower consumption



Battery capacity (%)	0	5	10	15	20
Base prob.	0.8794	0.8815	0.8958	0.9239	0.9485
Spike prob.	0.0304	0.0304	0.0304	0.0304	0.0304
Drop prob.	0.0902	0.0881	0.0738	0.0458	0.0211

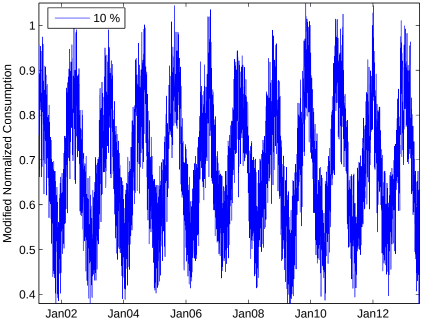
Battery



Battery capacity (%)	0	5	10	15	20
Base prob.	0.8794	0.8827	0.9066	0.9461	0.9763
Spike prob.	0.0304	0.0292	0.0196	0.0081	0.0025
Drop prob.	0.0902	0.0881	0.0738	0.0458	0.0213

Additional renewables, noise $U(-a, a)$

Renewables not as easy to control => negative consumption.



a (%)	0	5	10	15	20
Base prob.	0.8794	0.8696	0.8421	0.8013	0.7524
Spike prob.	0.0304	0.0349	0.0460	0.0624	0.0829
Drop prob.	0.0902	0.0958	0.1121	0.1360	0.1636

Table: Unconditional regime probabilities when adding *iid* uniform

What about short term forecasts?

Case: Charging electric vehicles (EV)

- When should we charge
- or decharge?

The daily models does not give us much guidence!

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What about an hourly model?

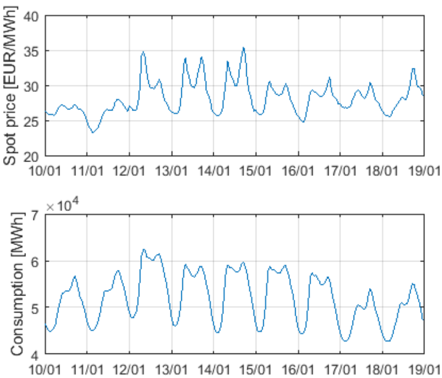
- Many variables tested (consumption, production, wind, reserve margin etc.)
- Dummies to handle certain effects

All parameters are stat. significant for all variables (data from 2009Q1 to 2013). However, Consumption is still the best variable

Variable	ℓ
Consumption	52225
Production	51381
Reserve margin	49100
Wind	49087

Case study, winter 2015

Can we predict extreme prices (normal week in January 2015)?
This is out of sample data!



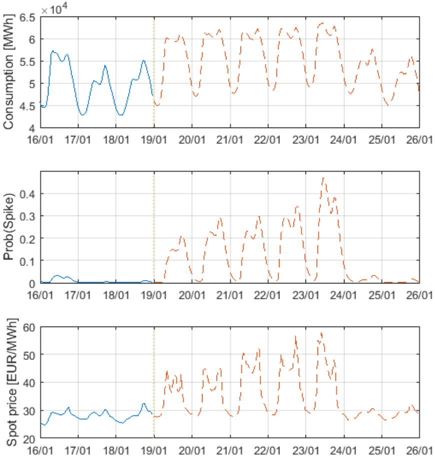
Saturday 10th to Sunday 18th in January, 2015.

Case study, winter 2015, II

Consumptions is easy to predict. Our case study is based on

- Forecast the consumption (here we use the actual consumption) between Monday 19th to Sunday 26th.
- Iterate the time varying Markov Chain using the forecasted consumption to compute the spike probabilities
- Compare the results to the actual spot price traded those days.

Monday 19th to Sunday 26th in January, 2015.



Note: The price varied between 25 and 35 during the previous week.

Summary

- Simple framework for evaluating the stability
- The stability is directly related to external factors
- There are few gains by using expensive batteries
- But, smart grid techniques seems crucial if more renewable are to be integrated.

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