Aalto University
School of Science

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Modeling Long-Term Electricity Prices

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Project Plan

Abstract

Electricity has special characteristics which make it different from other commodities. Since it cannot be stored, standard procedures for modeling the forward price fails to give accurate estimates of its behavior.

In this study we will develop a model for the long-term electricity prices with regard to the existing models and finding the statistical characteristics of spot and forward price data. This project plan briefly presents the central aspects of the problem as well as our goals in constructing a suitable model. The model estimation process, the workflow and courses of action are also discussed.

Background

Electricity is a commodity with special characteristics. As there exist no convenient and economic way of storing electricity, the prices of short- and long-term electricity contracts exhibit very different dynamics. Additionally, the consumption and production of electricity have to match at any time, which results in seasonal effects and causes high volatility and eventually high price peaks.

Predicting the long-term prices of electricity is especially important to the electricity retailers; as the long-term investments including considerable risks and accurate forecasts of future prices help companies to adjust their production. Usually forward and future prices of commodities can be modeled through spot prices, but this approach does not give satisfactory results for electricity derivatives. The spot price is highly volatile and hedging against this is important.

The Scandinavian electricity market possess its own distinctive characteristics — for example the peaks in the demand of electricity due to cold winter season and the dominant position of hydro power on the supply side. Different kinds of electricity derivates are traded at NASDAQ OMX Commodities Europe (formerly known as Nord Pool) for the Scandinavian market.

Nord Pool was established 1996 to attain a common electricity market for Norway and Sweden, and nowadays it also covers the markets of Finland and Denmark (Nord Pool, 2011). It is the largest power exchange in Europe, and the hourly spot prices tell the balance of demand and supply in the region.

However, our interest is in longer period future and forward contracts. They are purely financial contracts, so there is no physical delivery of energy at the time of buying and selling. Future contracts have usually shorter time horizon than forward contracts. We are intrested in the forward market, which consists of contracts of different lengths. In the case of *future contracts* payments are settled daily during trading period between the keepers of long and short positions. The final payments are done during the delivery period of the electricity. The financial payments of *forward contracts* are settled only during the delivery period, thus the profit and losses are realized only when the delivery of energy starts (Botterud *et al.*, 2002).

The dynamics of the electricity market have been studied quite extensively. Botterud *et al.* (2002) found that the risk premiums in the future markets are negative. Usually risk premiums are positive or zero in commodity markets. They discussed that the reason may lay behind the different elastics of demand and supply side of electricity market.

The problem of forecasting long-term electricity prices is far from simple. As discussed, the normal approach of using only spot prices is not relevant. Other independent variables must be included in the model, e.g. demand, factor prices and seasonality. Also the choice of the best model is not unambiguous. For example Cabero *et al.* (2003) assumed that the probability distribution of the electricity spot price resembles

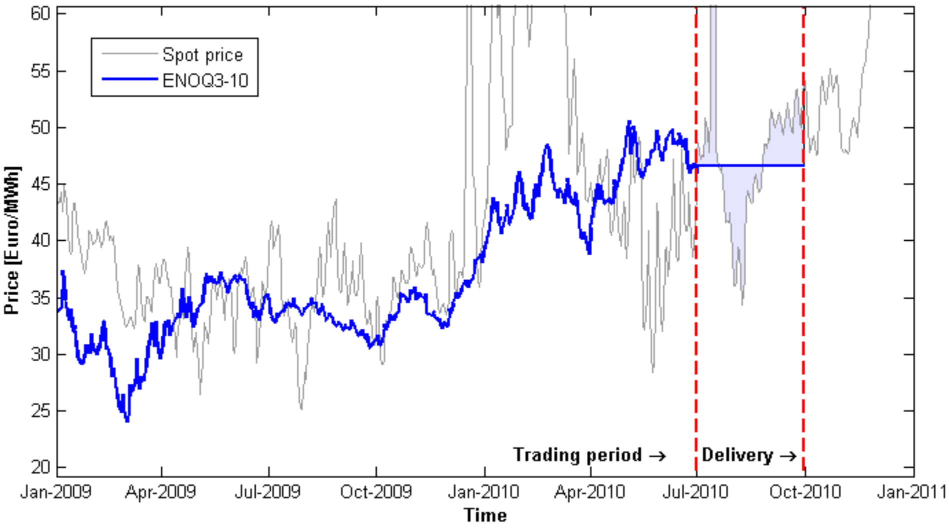

Figure 1: The price dynamics of a quarterly forward contract (ENOQ3-10) versus the system spot price. The high volatility can clearly be seen in both the spot and forward price.

the Beta distribution and used linear regression for fitting its parameters. Szkuta *et al.* (2002) have used a neural networks approach in short-term forecasting.

Haldrup and Nielsen (2006) and Haldrup *et al.* (2010) used a vector autoregressive model (VAR). In their model they explained the long memory of electricity prices with a SARFIMA model and used a switching model to model the congestions in the transfer system.

In modeling the long-term forward prices, Povh and Fleten (2009) and Povh *et al.* (2010) have been able to compose a satisfactory model. In their approach they identified variables affecting the long-term supply and demand of electricity and used them as explanatory variables adjusted with a risk premium. The risk premium was assumed to depend on the time to maturity. They argued that the variables influencing on the supply side of electricity markets are *fuel prices*, *water-reservoir level* in hydro-rich systems, *emission allowance prices*, supply capacity and electricity prices in *neighboring markets*.

The price of electricity is very volatile both in the short-term and long-term. Forward price dynamics are different from the spot price dynamics when the time to maturity is far from the observation time. As the delivery period closes in, the forward price dynamics becomes more similar to the spot price dynamics. The long-term forward prices are influenced by the long-term electricity spot price. Before moving to the model specification stage we need to build an understanding of short-term price and long-term price dynamics of electricity.

Goals

The purpose of this project is the quantitative modeling of long-term electricity forward prices. We limit our interest to long-term electricity forwards with a delivery period of one year and a time to maturity of more than one year. Contracts of longer time-spans are also discussed if possible.

1. Model specification

After getting a clear insight on the problem through background research, the next step is specifying the basic structure of our model. Our approach will be based on the work by Fleten et al. (see Povh and Fleten, 2009). A hard task is to determine which variables should be included in the model and what mathematical form such a relationship should take. Choosing the variables rely on previous work done in the field and on availability of data. In the approach by Povh and Fleten (2009) the indentified variables were forward prices of:

- Fuel prices (oil, coal, gas)
- Emission allowance prices
- Neighboring power markets

Additionally, demand and supply forecasts together with long-term weather and political influence are also discussed. Exotic and unexpected variables might be included due to the special characteristics of the power market (e.g. Fleten added the aluminum forward price)

2. Data analysis

Plenty of relevant price information and whole datasets are publicly available on the World Wide Web. We have understood that Danske Markets will assist us in the data acquisition process.

With many different data sources and different kind of data, one essential thing is to unify the data somehow. This means in practice downsampling and temporal smoothing of some kind — for example changing daily observations to weekly and using moving average smoothing.

Basic statistical analysis of the data is also needed. Stationarity and normality tests as well as getting the descriptive statistics of the sets are the next steps.

3. Parameter estimation

We will use a co-integrated vector autoregressive model (CVAR) for our modeling. Such a model is based on estimating the stepwise dynamics between many endogenous variables in a system, where also seasonal effects can be included with longer lags. There are a broad palette of ready-made Toolboxes and routines for this kind of estimation (e.g. for Matlab).

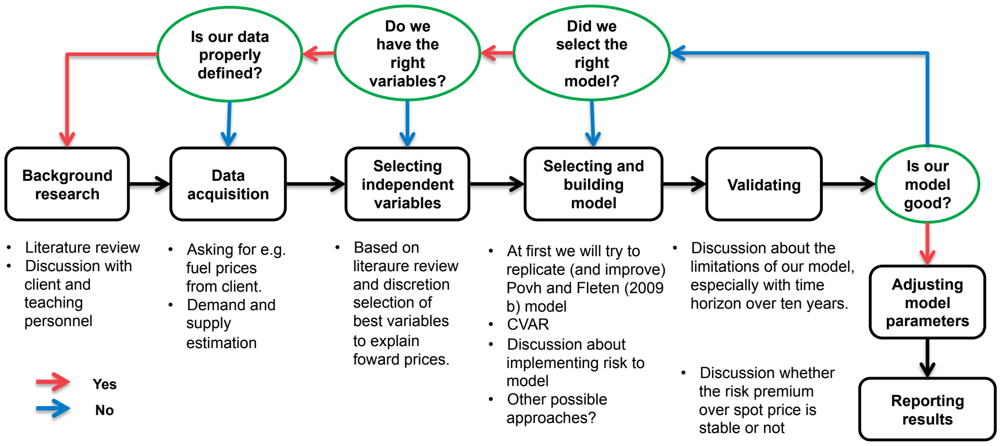

Figure 2: Courses of action visualized as a flow chart.

4. Model validation

Maybe the most important part in modeling is the validation of the model output. We will use the basic analysis of residuals and cross-validating the forecasting abilities of the model.

Courses of action

A basic flow chart model of the model building and validation procedures is shown in Figure 2. As there are four of us, dividing the tasks are challenging. Data analysis and parameter estimation can be easily split in tasks, but in order to unleash our full potential the goal would be to make the big decisions regarding the modeling together.

These decisions are discussed via e-mail and during our meetings. To gain further insight we have already discussed the topic with our client, Danske markets, and the course personnel. Contacting to some of the authors of relevant scientific papers has also been suggested.

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