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Electricity Price Models Are not Able to Predict Uncertain Expectations

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Summary:

Our paper looks for fundamental factors on the supply and demand sides which directly lead to the uncertainty of forecasting the prices on the electricity market. We tried to further develop various ideas of different authors. On the basis of comparing papers already published and analyzing electricity load and price modeling, we conclude that there are some risks connected with the legislative framework, weather and supply side curve, which are unforeseeable if combined. This paper was written as part of the solution of the research project of GAČR P402/11/0948 Developing an Analytical Framework for Energy Security: Time-Series Econometrics, Game Theory, Meta-Analysis and the Theory of Regulation.

Keywords: Electricity market modeling, electricity prices, liberalization of energy markets

Modely cen elektřiny nejsou schopny předvídat nejistá očekávání

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Abstrakt:

Článek se snaží nalézt základní proměnné na straně nabídky a poptávky, které přímo vymezují nejistoty předpovědi vývoje cen na trhu s elektřinou. Snažili jsme se navázat na představy řady různých autor a prohloubit je. Na základě porovnání publikovaných článků zkoumajících modelování spotřeby elektřiny a cen jsme došli k závěru, že existují konkrétní rizika spojená s vývojem legislativy, počasí a na straně disponibility elektráren, která nejsme schopni predikovat a pokud nabývají extrémních hodnot současně ani rozlišit. Článek vznikl také díky podpoře a jako součást výzkumného projektu GAČR P402/11/0948 Odvození analytického rámce pro energetickou bezpečnost: ekonometrie časových řad, teorie her, meta-analýza a teorie regulace.

Klíčová slova: modelování trhu s elektřinou, ceny elektřiny, liberalizace energetiky

JEL: O13, P48, Q41, Q47

Tento příspěvek je publikován jako stať.

Contents:

Introduction

In recent years, many papers analyzing electricity markets evolution have appeared. Our goal is to find the common and differing conditions taken into account by the authors of these papers. We will primarily try to analyze their methods and results, and compare them together, as well as with regard to the assumptions from which they arise.

In the following paper, we will try to sum up the main characteristics and drivers of the electricity markets from the viewpoints of the consumption (demand), supply, and the regulatory frameworks.

The main goal of our paper is not to recognize the perfect model, but to identify the implication relations from the individual levels of factors into the historical time series. Thanks to this approach, we would like to allow an uninitiated reader to create a better opinion. In accordance with this aim, we decided not to evaluate the outcomes of the authors of the individual papers, rather we tried to extract important facts.

We did not analyze only modeling and forecasting papers, but we also studied those papers which were focused on the market making. As a result, this should lead to a better understanding of the relations between individual factors.

1. Analysis of the Relevant Articles

This part is trying to resume a cross-section of articles from the past 10 years, and to analyze their outcomes. The most used models are, including descriptive analysis: Auto Regressive models (AR), Artificial Neural Networks (ANN), Markov Processes (MP and HMM), Jump Diffusion (JD), and Multi-frequency Analysis (MA).

1.1 Consumption Models

Benaouda et al. (2006) used 2 AR models: A multiscale wavelet-based autoregressive one (which is an AR model applied to data filtered using wavelet transformation) and AR. They also used 3 NN models: A multilayer perceptron neural network, Elman recurrent neural network and general regression neural network models. All models were used for only one-hour-ahead predictions. All NN models gave better results (the best one;the Elman RN resulted in a MAPE of 0.64% for Autumn, the worst MAPE was at 0.95% for Spring) than AR models (the best model – MAR: 0.73% for Winter as the best MAPE, 1.93% for Summer as the worst one).

Weron, Kozlovska et al. (2001) used generalized Ornstein-Uhlenbeck models (with AR, ARMA), where after the de-seasoning of data they found out that AR has got an absolute deviation of 59% higher than ARMA, on which they comment: "Observe that the above implies that the Vasicek model is a continuous version of the AR process." Another result of the model is that the prediction for the Christmas period is completely unsuccessful.

Abd (2009) used a framelet neural network for the consumption prediction, when the time series data are broken down by framelet (one scaling function and two wavelet ones), then the prediction using ANN is applied, afterwards the data are recombined to form the original time-series form. Load forecasted MAPE for week prediction is estimated between 1.8-2%, best for 5 days prediction, the worst one for 2 days prediction.

1.2 Descriptive Analysis of Prices

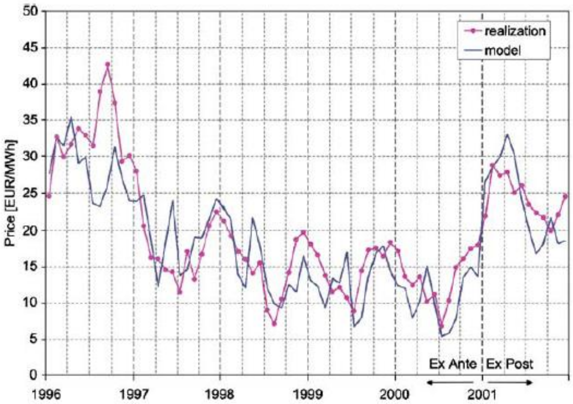
Weron and Przybylowicz (2000), on the basis of a Hurst R/S analysis deduced that the electricity prices are a mean reverting time series (i.e., they do not show random walk, and are not persistent ($0.5 < H < 1$); they are even anti-persistent <=> $0 < H < 0.5$). One of the characteristics of such a time series is that it follows a background trend, and in case of some temporal changes, to consecutively go back to following the main trend.

Weron, Bierbrauer et al. (2004) referred to two very similar models, solving 3 typical characteristics of electricity prices: Seasonality, mean reversion and jump behavior. Seasonality is solved by moving the average technique for the weekly cycle, mean reversion through a special type of AR. The probability of jumps is generated by the homogeneous Poisson process in jump diffusion models and a different scheme offers a regime-switching mechanism. The first one generates about 0.5% of a jump probability, the second one has 5.16 % of a jump regime probability (statistically they found a 1.6 % probability of a spike appearance at their definition).

On the basis of the observations of bids and asks on forward prices on the Nord Pool and of the predictions of a bottom-up model, Fleten and Lemming (2003) constructed "high-resolution forward price curves". The model used is based on the structure of the system (supply, demand), and on available data (snowfall, demand), instead of on financial models, which are, according to the authors, based on stochastic factors and data (market price). They modeled their approach in three ways: Term structure generation, maximum smoothness; where the smoothest parts of the function are used; and on truncated Fourier data, where, after seasonality modeling, the extreme time periods are taken away. While modeling 87 monthly products, the resulting average, the errors, expressed in percentages, were 2.7%, 2.87%, and 4 %. The best of the models, the TSG model, shows quite a large spread of errors (0-12.1%), which seems too much for modeling market data.

Vehviläinen and Pyykkönen (2005) studied the possibilities of Nordpool spot-price mid-term prediction based on a stochastic factors model (climate data, hydro balance, consumption and baseload supply). Firstly, they estimated climate data, to link them consecutively with data describing demand and supply, and in the end, they estimated the regression parameters of the model. The results can be seen in Fig. 1. The model copies correctly some partial trends, but it is unusable for trading purposes, seeing the errors, ranging in tens of percentage points.

Fig. 1: Usual differences between real and modeled spot-prices



Source: Vehviläinen and Pyykkönen (2005)

Here, Pipattanasomporn et al. (2002), described the differences between the competitive and regulated prices: "Prices for generation services in a competitive market may differ from regulated electricity prices, if competitive prices are based on marginal costs, and regulated prices are based on average costs", including the complete background and specificities of the energy environment in Thailand during the period of transition from a regulated to a competitive price system. They compare possible scenarios of evolution, depending on the chosen macroeconomic indicators (natural gas price, demand increase, capacities availability). They conclude that the competitive prices will be lower and more volatile than the regulated ones, and they also forecast typical diagrams of load and its typical coverage for Summer, 2003.

On the basis of executing AR analyzes of intraday and day-ahead trading, Longstaff and Wang (2004), found out that "forward premia are negatively related to price volatility, and positively related to skewed prices" (p. 1898). They also found that the volatility of prices is higher at day-ahead than at intraday trading, and add that up to articles from 2000. They also found that the

Californian market is different from the PJM one, so this conclusion may be only a general specificity of the studied region.

Concerning spot prices between 1993 and 2005, which include the whole period of the gradual Nord Pool enlargement, Bask and Widerberg (2006) tested the logarithm-difference of the prices Thanks to the Lyapunov exponents, they showed that during all the studied (operation) time, the exchange was stable (non-chaotic). In the case of filtering the outliers from the data, they discover that in the period of the accession of the Danish market, the energy exchange was unstable.

Mohammadi (2009) analyzed the co-integration relationship of prices of different energy commodities and electricity in the USA in the period 1960-2007. The author confirmed the co-integration only between hard coal and electricity, also thanks to the low usage of natural gas based generation plants in the USA during the long period under study. The estimated parameters suggested that "electricity prices are elastic with respect to coal prices, but inelastic with respect to natural gas prices".

His findings reflect the highly capital intensive nature of the electricity industry, as it requires heavy investment in the production and delivery processes. Thus, fuel costs comprise only a small fraction of the total costs. They may also reflect insufficient competition in the industry as electricity moves from generation to wholesale and retail distributions.

Chang and Park (2007) concluded from the analysis of the Singapore market-structure change:

- the impact of market structures on the electricity price and its volatility are economically and statistically significant
- DA and RT with vesting contracts are effective at maintaining a lower electricity price, while RT with vesting contracts is effective at lowering the volatility of the electricity price
- the effect of vesting contracts in lowering the price and volatility is more pronounced during peak hours

1.3 Auto-Regressive Price Models

Barlow (2002) worked with nonlinear Ornstein-Uhlenbeck (OU), simple OU and Schwartz models for the prediction of spot prices. On the basis of the estimation of the parameters, they concluded that the models used are more suitable (maximum likelihood estimation) than the Poisson and the hidden Markov process models, but they are stationary, so they cannot fully explain the relationship between the futures and the spot prices.

Cuaresma et al. (2004) tested various modifications of linear univariate TS models, as well as the AR, ARMA, Crossed ARMA, and unobserved component models (TS is broken down into long trend movements of series components, a cycle component modeled by a harmonic function with a constant frequency, seasonal component included by using a dummy and an irregular component assumed as white noise) for the purpose of making one-week predictions. They achieved the best results with the Crossed ARMA model with varying intercept, jumps and significance (only significant parameters were used), with Root Mean Square Error equal to 3.99 and MAE of 2.57.

Guthrie and Videbeck (2007) used periodic AR analysis to model prices. As a result, they showed on the intraday correlation structure that electricity is treated at different times of the day as being distinct commodities. By analyzing 8 years of half-hour prices they found that "the half-hourly trading periods fall naturally into five groups corresponding to the overnight off-peak, the morning peak, daytime off-peak, evening peak, and evening off-peak. The prices in different trading periods within each group are highly correlated with each other, yet the correlations between prices in different groups are lower." They also concluded that "shocks in the peak periods are larger and less persistent than those in off-peak periods, and that they often reappear in the following peak period. In contrast, shocks in the off-peak periods are smaller, more persistent, and die out (perhaps temporarily) during the peak periods."

The article from Diongue et al. (2008) is dedicated to the modeling of spot prices on the EEX, with special regard to the volatility by concentration on the conditional mean and conditional variance, with the dynamic k-factor GARCH model. From the presentation of 2 weeks evolution of spot prices, there is described mostly a very high fluctuation of prices during peak periods. The extreme size of these fluctuations is also highlighted by the results of the modeling, when the estimations of the peak periods show much worse estimations (RMSE 3.6-6.0, 8.4-18.0 on the best model– the 3-factor GIGARCH one) than at the beginning and at the end of daylight and during the night.

1.4 ANN Price Models

By using an adaptive model, calibrated on the data sample in order to better specify the model on a weekly basis by comparing it to the real prices (updating the weights), Yamin et al. (2004) found that for estimating the weekly predictions, the model has low accuracy. To test and compare it, they used three simple methods. It is interesting to note that the method presuming linear dependence between the load change and the price resulted (seen the MAPE) only a little bit worse than the studied ANN models (6.44 adaptive, 7.65 alternative method, 8.12 non-adaptive ANN), while the MAPE in this article was re-defined (they used the median instead of the average).

Hu et al. (2008) used a 3-layer ANN for day ahead and AR models for week predictions. The MAPE resulted in a spread between of 9.7 – 19.1 %. For the week prediction, the error of the forward prices came out similarly (8.97% - 19.47%). From among the interesting ideas put out by the authors, we can quote the usage of MRR as the most important factor of the game theoretic adjustment. It is a pity that they did not succeed in including it well into their model, as we can see with the ANN prediction that was not able to cope with the short term decrease of prices in the hour when the load fell down.

A three-layered feed-forward neural network, trained by the Levenberg-Marquardt algorithm, was used by Catalão et al. (2006) for forecasting the next-week electricity prices. For comparison purposes they used the ARIMA model. In every period, ANN seemed to be the better predictor. For spot electricity prices on the Spanish market, the MAPE resulted in Spring 5.36%, Summer 11.40%, Autumn 13.65%, Winter 5.23 %, and in California in Spring 3.09% which is the best forecast in this paper. From the comparison of figures 5 and 7 in the paper under study, we can say, that ANN didn't capture the bigger price volatility in Autumn.

1.5 Chaos and Wavelet Models of Prices

On the basis of historical data, regional reference prices, consumption, and availability of sources, Lu et al. (2004) used two forms of prediction: The first, a classical one which uses wavelets and ANN for a standard forecast, and the second one, using data mining for spike forecasts (while the probability was set on the basis of an index relative to the size of the reserve, with regard to the demand, and relative changes in demand, regarding the reference moment of the day). The classical forecast results were with errors between 2 and 5 %, afterwards, including a forecast of the peaks, the errors were better than 50%.

Unsihuay-Vila et al. (2009) used an evolutionary strategy combined with a chaotic nonlinear dynamic model for one week predictions, and compared it with ARIMA and ANN. It is interesting to see, how much various methods react with similar sensitivity to different time series (with the exception of unstable markets like New England). For example, in Autumn in Alberta, the ECHM had MAPE of 0.745 %, ANN 0.82 % and ARIMA 1.5%, but in Summer in Spain ECHM 8.691, ANN 8.720, ARIMA 8.73.

"The proposed approach PREDICT2-ES is capable of effectively capturing the complex dynamic (without strong spikes) of the time series, since in the real time series, this dynamic complex is unknown; i.e., it can be any chaotic, stochastic, etc., or a combination of them."

1.6 Price Processes

Yu and Sheblé (2005) use HMM for making mid- and long-term forecasts. They compare 4 sorts of models – simple regime switching (between market states), factorial (presuming that the consecutive state depends only on the former one represented by the price and three factors, on which the price depends: The level of demand, the level of supply, and the quantity of ancillary services. They also presume 3 main basic states: The growth "punch-in" state (if demand ≤ capacity(n − 1)), the harvesting state (if capacity(n) ≥ demand ≥ capacity(n − 1)) and the ripping-off state (if demand ≥ cap(n)), where n is the number of available sources. The result is that they counted the probability distribution of the transition from one state to another for all the included variables. We did not find any verification comparison between the forecast and the reality, as they conclude: "The application of probability theory enables the HMM to be estimated and solved efficiently. The HMM provides modelers the capability of modeling the electricity market structure, architecture, and market participants' competition strategies within an integrated framework."

Because of the irregularities studied on 48 trading periods of the day, let us take note from Karakatsani and Bunn (2008) that: "Firstly, spot prices are influenced by a mixture of factors, including economic fundamentals, plant constraints, strategic behavior, perceived risk, trading inefficiencies, learning, and market design implications. The intensity of these effects across markets is expected to depend on the specific market configuration. Secondly, all effects exhibit substantial intra-day variations, in terms of magnitude and significance, which reflects the diurnal heterogeneity of scheduled plants, as well as market design aspects (…) Thirdly, transient pricing irregularities, manifested as spikes, exhibit an interesting property; on these occasions, strategic factors appear to be significant and much more influential, whereas the impact of cost-fundamentals is constrained compared to the normal pricing regime. Hence, the magnitude of spikes, despite the diversity of underlying causes, is not arbitrary. Instead, it demonstrates a recurrent and coordinated generators' reaction to scarcity, whenever this arises and irrespectively of its exact source."

Higgs and Worthington (2008) used two basic stochastic models: Mean-reverting and regime-shifting models. In both they use one deterministic and one stochastic component. For the Australian markets, they quote the government "Securing Australia's energy future (2004)", where 3.2 % of the year, there are spikes, and they comprise 36% of total spot market costs; the article does not confirm such a low frequency of spikes.

Daily spot prices from 1999 to 2004 show that the regime-switching model outperforms the basic stochastic and mean-reverting models. Electricity prices exhibit stronger mean-reversion after a price spike than in the normal period, and price volatility is more than fourteen times higher in spike periods than in normal periods.

2. Specificities Of the Market With Electricity

In the previous chapter, we analyzed the problems and conclusions of the different approaches to study and model the electricity market. Now, we will try to describe the main facts, problems and causalities that one can meet when modeling the market with energy. We will not directly refer to the specificities from chapter one, we had better focus on a complex presentation based on the three main levels that depict the market with electricity.

The first level is the energy industry environment, in which the main task of the producers to supply electricity and heat to the consumers is fulfilled. Among the consumers, we can also include industries as well as services, public administration, and households. The second level is observing the players acting on the market, together with the analysis of the spheres and areas of influence to which they are subject. The third level is the energy exchange which gives us a partial image of the prices of traded electricity, and the ways of trading used by the various players.

2.1 Power Industry

At the beginning of electrification, plants were constructed to supply the energy locally to close-by factories and businesses, city agglomerations, as well as to separate localities. In the fullness of time, they connected to regional entities with only limited connections. These developed within the parameters of frequency, and of the current, thus providing short-term back-up to other systems in case of need.

The industry has recently undergone many changes, while most of them were set to be, later, a deregulated industry. Deregulation of the electricity industry breaks the vertically integrated utilities into horizontally independent entities, by which the market environment is allowed to sell and to buy a limited quantity of electricity across the whole connected system. Of course, in practice, there still exist local monopolies – in geographically and politically delineated regions – and also closer mutual links, which is mostly accountable for by the electricity transmission grid limits between the individual transmission networks. But further development of the networks leads to the elimination of these limits.

The independent entities are the buyers, sellers, and coordinators of the electricity markets. The market participants own and operate different parts of the electric power systems, which defines the electricity markets structure. We are also able to find market participants with unequally defined rights and obligations, between which we can count the transmission and distribution systems operators, the market operator, and eventually the exchange.

The individual entities are gradually led to further development in the areas entrusted to them by the application of generally valid directives, observance of which is a condition for participating on the market. On every market, we can find some producers, competing mutually on the demand side, the demand itself does not change substantially during the year. The regulatory framework is given by the directives of the EU, as well as national legislation, which are prepared by an administration set up for this purpose. These legislative texts include not only the rules governing mutual relations between the electricity market participants, but on some markets there is also an important regulation defining the prices for final customers. This one consists of a regulated component, including certain fees related to the operations and the development of the system, as well as by free values derived from the price of the power.

The commodity, electricity, cannot be stored; it is consumed at the same time as it is produced. Electricity supplied at two different times at the same quantity most probably does not come from the same sources, and therefore most probably does not have comparable costs. This is given, firstly, by its physical essence, as electricity behaves according to the so called Kirchhoff laws, and secondly, by the possibility of cutting off a source of energy at a certain hour and to buy the same output from a different available source. This leads us to analyze the behavior of prices in individual cases.

2.2 Market Forces Defined By the Players

The individual players should be followed separately on the sub-markets corresponding to the individual geographically and politically delineated regions with different market players.

From the short term point of view, we can watch the market from the aspects of supply and demand. On the supply side, we generally find suppliers of fuel to the plants, the individual plants themselves, and the portfolios of those plants. The demand is characterized by a consumption diagram, which shows some socio-economical characteristics from the point of view of the year, week and of the day. For instance, we can say from the point of view of the day that the load is lowest in the early morning hours, and it is highest between noon and the early evening. In every region, we can find a different structure of plants, depending on the availability of fossil fuels, usability of water courses, the political will to use nuclear, natural gas or renewable sources of energy. In general, there is a tendency to cover the basic part of the diagram with the cheaper sources, and to switch to the more expensive ones when the need for supplementary output arises.

If we begin to think only about the individual plants, we can divide the players into base-load generators, which are mostly nuclear and hydro plants, and some coal plants; and into peak-load generators, that are mostly coal and natural gas sources, bidding on the market on the basis of the price of the fuel (dark and spark spread), as well as pumped storage hydro plants. The costs of coal plants are influenced a lot by the long term contracts on coal supply from the available mines, and lately also by the price of the CO_2 permits.

There are also some other specific players on the market – the producers of renewable energy. Their development is financed by the subsidies given to investment and operation costs, thus allowing them to compete with the traditional sources. The small hydro plants are mostly run-of-river power stations, i.e., they produce energy with a stable quantity of power throughout the year. Solar plants are also active throughout the whole year, and they produce mostly during daylight hours, with good climatic conditions. They reach the highest output around noon during sunny days. The wind power plants can be divided into offshore and onshore, they supply electricity throughout the whole year if good wind conditions prevail (according to defined ranges of wind velocity). The supply from solar and wind sources demonstrably increases the cost set off for the system regulation; it increases the need to regulate sources.

The presence of pumped storage hydro plants is very valuable for the particular regions, in the case of a local consumption minimum, or of an unexpectedly strong positive production shock to consume some electricity from the system, and in the case of a source outage, or of peak consumption, to generate electricity. The power plant reaches its maximum output within tens of seconds from its start-up, and so, it practically eliminates the minimum and maximum consumption difference.

If we sum up the abovementioned, a supplier mainly considers the following factors when making a decision: the forecast load, the costs and capabilities of its own generators and those of its rivals. These factors may show a certain degree of periodicity but not inherently so.

In the short term (day, week), consumption shows up as stable, as has been said in the beginning of this part. The day and night, week days and week-ends variations of consumption are not difficult to find. In the longer term(months, years), we can already find substantial changes.

The demand changes by factors from inside or outside. The inner factors are mostly socially influenced (change of behavior, e.g. using appliances in cheaper time zones, using new and more modern appliances), and economically influenced (switch to energetically less demanding production technologies, heating, central heating). Outer factors influencing the demand include e.g. the legislative framework (exclusion of energetically more costly, or products with higher consumption) or by motivation emerging from the demand side to use more modern products and technologies through subsidies or taxes.

As an important indicator of the evolution of consumption, we can cite the variations of the share of individual industries on the GDP output, as the energy intensity of the industries, without any substantial technological change, seems relatively stable with regard to the per unit production. As a general trend; and not only in the EU; since the oil crisis, we can see the shift to less energy intensive industries, and to transfer the more expensive production processes to regions with cheaper production factors, mainly the labor force. From this, we can deduce the long-term changes of both the level and the structure of the demand: energy intensive industries disappear (from the more developed countries) and are replaced by services or by high-tech and highly qualified production industries. The results include the increase in the cyclicity of the demand (heavy industry used to consume – without larger fluctuations – throughout the day, and other time periods, while services and households have short-term cyclical consumption).

At the same time, we must mention that, notwithstanding the abovementioned routinely established processes of decreasing the energy intensity and the incentives for the changing of consumer behavior, the demand for electricity steadily increases, which that the issue of ensuring of supplies in the long term remains topical.

The market forces will show up mostly in real time, as there are different ways of covering electricity consumption, which are set by the actual availability of the sources and by their production costs. With the result, the market can seem very complicated, but if we take into account the long-term contracts between the producers and the consumers (or their representatives), whose only aim is to be protected from the risks on the side of the production and supply, we will find an easily readable process in the mid- and long-term process of preparing the production and supplies.

The basis of this process can be seen in the diagram of the expected consumption (load) in the chosen regions at the level of several days, weeks, months, one or more years. This assumption, which of course differs for different market players, consecutively leads to the distribution of the necessary maintenance in the respective time horizons in the most effective way. The producers adapt to the continuously changing prices, in order to find the optimal surface of the diagram for every source, which allows them to achieve the maximum possible profits.

The market force, defined as the rate of control over, or the level of influence on, the final price, is derived mainly from two factors.

The first factor is the costs per produced unit that supplies electricity into the network (marginal cost), which differs for various types of plants. The weaker players can be defined, not by the size of production, but exactly by the actual marginal source(s) with the maximum as the high costs which are available for the as yet untraded output.

As the market, on which every plant would represent a different player, is more a dream than reality, it is usually not necessary to include all the plants to deduce the market force; it is sufficient to identify the dominant players which cover the majority of the consumption, which substantially simplifies the reasoning for us. We can also say that a higher the number of players leads to lower prices of electricity for consumers, as is shown in Pipattanasomporn et al. (2002), that the competitive prices based on marginal costs will be lower and more volatile than the regulated prices, based on average costs .

The second factor is the Must Run Ratio, which identifies selected sources as those that cannot be switched off for specific reasons (heat supplies, allocation of services allowing the regulation of output in the system). The owners of such sources are willing to sell – in the short term – for a price not corresponding to the costs.

The paragraphs above can be summarised in the following quotation: The aggregated online generation capacity at the next time interval depends solely on the current level of online generation capacity and the unit commitment and dispatch decisions of GENCOs. Due to the limited transmission capability and its non-storable nature, electricity is heterogeneous between different locations and time intervals. This leads to segments of electricity markets depending on time horizon and electrical distances. By this, we have summed up and explained the basic processes defining the functioning of the market with electricity.

2.3 Trade with Electricity

From the short term point of view, electricity is traded on the daily market (on the D-1 day or the closest working day before the day D) and on the intra-daily market (opened after the end of the daily market), its principle being the auction. The market is meant mostly for the needs of the dispatching of the TSO for the latest updating of the setting of the sources and networks.

From the long term point of view, the exchange helps to tackle the transactions, whose product is the base-load (24 hours of each day of the traded period) or the peak-load (8.00am-8.00pm of every day of the traded period), traded for periods of a week, a month, three months, a year, and for a maximum, roughly, of three years. We distinguish the following contracts: Forwards (two-sided agreement, also out of the exchange, at which the settlements happen on the day of supply), futures (two-sided agreement, at which the regular settlement happens through the market-to-market settlement), options (right to acquire energy in the agreed period for the agreed price), and contracts for the difference (hedging against the difference of forwards/futures from the spot price in the region of the supply). Another way of trading is also by using the services of a broker.

A very important part of the trading is the calculation and the financial estimation of the deviations, calculated by the market operator, and in which the deviation from the agreed output and the actual supplied output are adjusted. The operator receives the information on the physical flows from the DSO or the TSO.

Regarding the profits from trading at the exchange, Longstaff and Wang (2004) concluded that forward premia are negatively related to price volatility and positively related to skewed prices. They also found that the volatility of prices is higher for day-ahead trading than for intra-day trading.

As the last important domain of trading, we can mention cross-border trading. On the basis of the agreements between the TSO's, explicit auctions on the right to use the free cross-border profile before the given day or hour has been established. As an example, we can mention the Central Allocation Office in Germany. This auction is not related to any concrete supply of energy, and so it happens that the sold capacity does not correspond to the actual transmitted quantity of energy; and even the direction of the traded flow of energy does not have to correspond to the resulting real physical flow. This problem is solved by the implicit auction, at which not only the TSO's participate, but also the energy exchanges and market operators. This auction offers to buy electricity including the needed profile one step at a time.

The given information on trading is very generalized, and it is not the main subject of this article; for detailed rules of trading, we refer to the web pages of the individual exchanges, auction agencies, and market operators.

2.4 The Form Of the Electricity Spot Price Curve

By the analysis (Cuaresma et al. (2004)) of the time-based development of the spot price in the past, it has been shown that electricity spot-prices represent several types of superposed seasonal cycles, mean reversion and price spikes, so there are characteristic places – from the point of view of the year – with high and low prices, that the price has the tendency to revert to a certain level at certain moments, and that at certain periods, regular consumption peaks take place. Also Weron and Przybylowicz (2000) confirmed that the prices of electricity are time-reverting time-series, and that they are also anti-persistent.

From the short-term point of view of the Leipzig exchange, the above mentioned Cuaresma et al. (2004) found the following: Prices are significantly higher during weekdays, and both for weekends and weekdays a relatively similar intraday pattern emerges: the price begins to increase at around 05:00 during weekdays (07:00 for weekends) and continues to increase until 12:00 when there is the first and biggest peak of the day. Then the price begins to fall until 17:00 and, after reaching its locally lowest point, it starts to increase again until 19:00–20:00 when it reaches the second peak of the day. Prices begin to fall thereafter, until the 05:00 (07:00) turning-point re-appears. Guthrie and Videbeck (2007) concluded that electricity spot prices exhibit long memory behavior combined with a periodic behavior. We would expect that this would lead to a relatively stable trading on the market. Thus, electricity price movement shows very great, actually the greatest, volatility of all commodities (Yamin et al. (2004)).

Classical economics would explain this as the existence of a high excess demand over supply. If we begin to think also about the dynamics of the model, unplanned phenomena instantly enter the game. These unplanned phenomena are outages, disturbances, and malfunctions of sources and transmission networks. Through an outage of a transmission network, the group of available sources can change, and thus we can experience a large shift of the supply curve to the left. The accumulation of several outages of sources over a short time horizon can lead to a similar scenario. A substantially lower effect would be caused by cutting off or connecting a source (planned or not). Another idea regarding the spikes from Cuaresma et al. (2004): "Such a phenomenon is usually explained by either supply sided (unplanned outage of a large power plant) or demand-sided shocks (heat wave in Summer). On the other hand, also market mechanism failure and capacity constraints of the network can cause spikes, because they lead to temporary deviations from perfect competition in the market and therefore to price spikes when temporary monopolists or oligopolists make use of their market power." In other words, we could find a situation when a producer is waiting till the last possible moment to trade, in order to raise his profits. The costs of an alternative producer in case of a failure of a pre-contracted supply are equal to the costs for the deviation in the system, and they are much higher than the usual spot price. The costs of a producer in the case of failing to supply the pre-contracted electricity, are equal to the costs for a deviation in the system, which are substantially higher than a normal spot price, and that is why the same producer is willing to demand his outage for a much higher price than the one corresponding to the marginal costs of an alternative producer.

The opposite situation of a temporal dis-equilibrium on the market often leads to the fact that the clearing price is often below zero. For a dominant player, it might be profitable to not to switch off a source, given the costs of switching it on again, and therefore, he is able to sell at a much lower price.

Another argument is brought by Guthrie and Videbeck (2007): "The prices in different trading periods within each group are highly correlated with each other, yet the correlations between prices in different groups are lower." and also "shocks in the peak periods are larger and less persistent than those in off-peak periods, and that they often reappear in the following peak period. In contrast, shocks in the off-peak periods are smaller, more persistent, and die out (perhaps temporarily) during the peak periods."

2.5 What Influences the Price Of Electricity According To the Authors Of the Articles Under Study?

Every article under study examined a slightly different set of quantitative and qualitative variables, while the weight of the same variable in every two models differs up to the studied market and the studied time period. We have chosen some forms of ideas, which are interesting to think about.

The first one, from Yu and Sheblé (2005), comes from the idea that the technology of generation, transmission, storage, and consumption of electricity determines the time-varying and space-varying prices of electricity in all segments of the electricity markets, and that we could think differently, given the connection of the markets. The validity of this opinion can be found in the capacity limitations of the transmission between the systems. A substantial part of consumption is produced from local sources, and only the upper range of the load diagram is partially covered by sources from neighboring systems (from the historical point of view, the transmission networks are not designed for international trading, but for emergency assistance). This idea is confirmed also by Knittel and Roberts (2005), up to which the main factors impacting the electricity price are generator availability and generator bidding strategy on the generation side. This gives us two concrete factors for modeling the price: The first one is the availability of sources, which is the question if a local producer has a source available that is cheaper than the price of another source in one of the neighboring systems, if the parameters of the network allow the supply. The second factor is the plan of necessary maintenance of sources, which in the mid- and long-term perspective delineates the group of sources available in the region.

Another influence is using the 4 following input factors: time factor (day of the week and hour of the day), load factor (system load and bus load), reserve factor (spinning and non-spinning) and line factor (line status, line limit). If we watch the price from the point of view of an aggregate producer, we logically deduce, through the combination of these factors, some explanations of the moves of the electricity price as depending on the necessity to cover the actual consumption (as we explained formerly in the part describing the market force).

Knittel and Roberts (2005) also wrote: "Specifically, electricity prices display the following distinct characteristics: 1. stationarity in both the price level and squared prices, 2. pronounced intraday, day of week, and seasonal cycles, and 3. extreme price swings in a short period of time, 4. censoring from above, 5. negative prices." We can also quote for the main characteristics of the market data: "1. mean reversion, 2. time of day effects, 3. weekend/weekday effects, 4. seasonal effects, 5. time-varying volatility and volatility clustering, and 6. extreme values."

Another observation worth mentioning is from Unsihuay-Vila et al. (2009) is that electricity demand seems random, but some believe that it seems chaotic, due to the influence of many complicated factors such as temperature, price of electricity and many others. Similarly, the price of electricity depends on the supply and demand aspects of the market and the operating conditions of the transmission network, which are influenced by such factors as the climate, the economic situation, the planning for development, accidents and failure. The joint effect of these factors results in complicated dynamics of electricity demand and price. The authors of this chaos evolutionary model, which they tested for short-term predictions, presume that there are too many factors, which cannot be taken into account in the framework of the model.

Aggarwal et al. (2009) summed up the conclusions of a range of prediction models of consumption and price. One of their conclusions states: "In actual electricity markets, the price curve exhibits a considerably richer structure than the load curve and has the following characteristics: high frequency, non-constant mean and variance, multiple seasonality, calendar effect, high volatility and a high percentage of unusual price movements." This sums up all the main problems that all models have to cope with.

Through this short listing, we are trying to show that even if a large majority of authors realise quite well that all the problems brought on by the modeling and predictions of electricity prices (they describe them in slightly different forms), they do not try to raise questions about the structure of the market and the publication of information, and about communications between the market participants. There is no obligation to publish information on the states and availability of plants and networks. Neither is it compulsory to publish information on expected outages. However, this information would lead to cheaper electricity for the final consumer. It is a market failure according to classic economic theory.

Conclusion

As well as Aggarwal et al. (2009), who analyzed 47 papers on electricity markets modeling, our paper also went through a number of studies on this topic. In general, we can conclude that:

- Although we are able to predict the load with a high degree of precision, whenever there are some risks in relation to the weather together with risks on the supply side, it can cause much higher disturbances to appear, than the models would otherwise assume.
- If there is no information available on the market, containing very precise online data, traders cannot work with a prediction that is exact enough to foresee the behaviour of the market. The insufficiency of fundamental analysis seems to be evident.
- Price spikes, both positive and negative, are the only consequences of the impossible definition of the correct marginal power plant. It is clear that these (spikes) are given by the bias between high frequency forward prices and subsequent spot prices.

Basically, we could compare the individual methods of modeling, but we prefer to compare the data that they were working with. If we abstract from price spikes, most models have a similar capability for forecasting spot prices evolution, and their success is influenced more by the data sets analyzed. Spot prices in the countries or time periods with a lower participation of renewable sources, and with a higher share of classical fossil fuels power plants display a lower variance.

Models working with low frequency forward prices are precision-dependent on the tendencies of the long-term expectations of the market. These expectations are partially irrational. In the best case, they are only dependent on the mid- or long-term weather predictions, and thus on the assumed consumption. Lately, we could remark that some risks connected with the legislative framework of the market, expected developments in the transmission system network, new (mostly renewable) sources installation, and older sources attenuation (e.g. German nuclear plants moratorium), are high and cannot be forecast with any degree of accuracy.

Last but not least, for high quality forecasting of models of the high frequency time series, enough historical data are important. Because of the unstable legislative and regulatory frameworks governing the electricity markets, these models cannot be sufficiently well calibrated. This is given by the fact that the liberalization process is in its infancy, and we strongly believe in the tendency towards market stabilization.

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