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Agent-based modeling of oligopolistic competition in the German electricity market

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Summary. This paper reports results from an agent-based simulation model that comprises a day-ahead electricity market, a market for positive minute reserve and a carbon exchange for CO_2 emission allowances. Agents apply reinforcement learning and optimize trading strategies over the two electricity markets. Simulated results are closely similar to empirically observed prices at the German power markets in 2006. This makes the model applicable for analyzing different market designs in order to derive evidence for policy advice.

Keywords: agent-based modelling, oligopolistic competition, reinforcement learning, interrelated markets

1 Introduction

Several interrelated markets play a role in the electricity sector. From a short-term (daily) trading perspective, markets for day-ahead scheduling and for real-time dispatch or balancing energy, as well as auxiliary markets e.g. for CO_2 emission allowances are most prominent. Some participants have the potential to exert market power in several of these markets, given the oligopolistic structure of present-day electricity systems. These factors make electricity market modelling very complex. The agent-based (AB) modelling methodology offers great flexibility of specifying complex scenarios and may be a valuable tool for market analysis and design in the electricity sector. AB simulation models can be used as fully controllable virtual laboratories for testing economic design alternatives in order to determine the market designs that perform best in an environment of selfish agents [Tesfatsion 2006]. This approach follows the postulation formulated by [Roth 2002] that markets should be designed using engineering tools, such as experimentation and computation.

Several agent-based approaches for wholesale electricity market modelling have been described in the literature, e.g. [Bower, Bunn 2001], [Nicolaisen, Petrov, Tesfatsion 2001], [Bagnall, Smith 2005], or [Sun, Tesfatsion 2007]. The contribution at hand presents a model of the German electricity sector that aims at contributing to the challenge of analyzing market interrelations in the electricity sector and may serve as a tool for engineering power markets.

2 The Model

The simulation model presented here comprises three markets: a day-ahead electricity market, a market for balancing power at which positive minute reserve is traded, and an exchange for CO_2 emission allowance trading. Market participants are modelled as adaptive software agents who develop trading strategies through reinforcement learning (here Q-learning). The agents face the problem of trading on these interrelated markets. A more detailed description of the simulation model is provided in [Weidlich, Veit 2008a].

Markets are interrelated only through the agents' trading strategies. When searching for profit maximizing bidding actions, agents consider opportunity costs, i.e. foregone profits that they could have realized on the other markets. Through this procedure they coordinate the bids they submit on all three simulated markets. The strategies that agents can choose from on the considered markets are described in Section 2.1, and the data input for the simulations presented here is specified in Section 2.2.

2.1 Markets and the Agents' Strategies

Agents act strategically both on the day-ahead market (DAM) and on the market for minute reserve (balancing power market, BPM). Besides, they place price-independent bids on the market for CO_2 emission allowances with the volume corresponding to their daily allowance need (buying bids) or surplus (selling bids).

The demand side of the day-ahead market is represented as a fixed price-insensitive load. Data of the hourly system's total load is used for representing electricity demand. In the short-term, the assumption of a fixed load is realistic, because electricity consumers usually do not have any price information at short notice that would allow them to adapt their consumption to the price signals. As the questions treated here focus on short-term market dynamics, fixed price-insensitive load is a valid assumption.

Agents learn to submit profit-maximizing price-volume bids on both the day-ahead electricity market and on the balancing power market. As reinforcement learning is used for representing the agents' search for the optimal bidding strategies, the set of possible bids must be specified in advance. The definition of the domain of possible bids is a sensitive task and should be calibrated so that real-world prices are reproduced as closely as possible. As a bid on the day-ahead market contains an offer quantity and a price at which this quantity is offered, the action domain on the day-ahead market comprises the two dimensions of prices and volumes. In the present model, agents can submit bid quantities expressed as a fraction β of their available capacity; possible fractions are set between 0 and 100 % in 20% steps; bid prices are set to the range from 0 to 100 EUR/MWh in 5 EUR/MWh steps. The resulting action domain is specified as follows:

$$M^{DAM} = [p^{DAM}, \beta^{DAM}] = [\{0,0\},\{0,0.2\},...,\{100,1.0\}] \quad (1)$$

On the market for positive minute reserve (balancing power market), a predefined quantity of positive minute reserve is procured. Six equally long bidding blocs of four hours length are differentiated for every trading day: from 0 to 4 am, from 4 to 8 am, and so forth. The tendered balancing capacity quantity Q_k^{BPM} is equal for every bidding bloc *k*.

The domain of possible actions on the balancing power market contains the two dimensions capacity price (*cap*) – the price for holding capacity in reserve over the whole bidding period – and energy price, i.e. the price a generator is paid for produced minute reserve in case his plant is actually deployed for regulating purposes. Possible prices range from 0 to 200 EUR/MW in 21 discrete steps for the capacity price and from 0 to 100 EUR/MWh in five steps for the energy price. This leads to the following action domain:

$$M^{BPM} = [p^{BPM,cap}, p^{BPM,energy}] = [\{0,0\},\{0,25\},...,\{200,100\}] \quad (2)$$

Agents learn strategies separately for the day-ahead and for the balancing power market. In the implementation, they have individual instances of the learning algorithm for each of the two markets. Moreover, strategies for each bidding bloc on the balancing power market and for each hour on the day-ahead market are learned separately.

For some types of power plants, the possible actions an agent can take differ from the action domains presented in Formulas (1) and (2). Nuclear power plants and lignite-fired power plants, for instance, do not allow short-term load changes, but have to be kept at a relatively constant or slow-changing power rating. Therefore, it is not realistic to assume that these power plants are deployed for strategic bidding of hourly power delivery on the day-ahead market. Output from these power plant types are, thus, bid at their respective marginal generating costs. Furthermore, it is assumed that weather forecasts are not yet precise enough for predicting the output power of wind energy converters in every hour of the following day. Consequently, electricity from wind energy can not be bid strategically at the day-ahead market. For taking into account the electricity amount produced by wind turbines, the installed wind energy capacity of the basic scenario year (2006) is multiplied with yearly average full load hours for estimating the capacity that is available in every hour. This quantity is bid into the day-ahead market at a bid price equal to the marginal cost.

Only few power plant types are suitable for delivering minute reserve. These have to allow fast changes in load and must be ready to be fully activated within

15 minutes. In the simulation model developed here, only gas-fired power plants and hydro-power plants are assumed capable of delivering minute reserve; for simplicity, no distinction is made between gas turbines or combined-cycle power plants. Power output from all other plants can consequently only be bid on the day-ahead market, and opportunity costs from the balancing power market are not considered for these plants.

The CO_2 emission allowance market is modelled as a sealed bid double-auction that is cleared at the end of each trading day. Each agent submits one daily bid on the allowance market, representing its allowance requirement or surplus for the specific day, which is calculated for the whole portfolio of power plants it owns.

All generator agents that own fossil fuel fired power plants are initially endowed with a certain amount of CO_2 allowances. The initial allocation of allowances is calculated according to a grandfathering rule, i.e. based on past emissions for each single power plant. The sectors outside the electricity industry that are covered by the emissions trading scheme submit a fixed supply and demand every day. As little is known about CO_2 mitigation costs of these sectors – and consequently about their valuation for certificates – their supply and demand is calibrated so that average prices that arise endogenously during the simulation roughly correspond to observed prices in the real-world carbon exchanges.

It is assumed that all agents seek to even up their open positions every day. This entails that agents who sell electricity also make sure to have enough allowances for the carbon dioxide emissions associated to their generation output. Speculation is not considered in this model. The agents' daily trading quantities are calculated on the basis of initial endowments and of trading success on the current trading day. The amount of carbon dioxide emitted during electricity generation is determined by the electricity amounts sold at the day-ahead market and by deployed minute reserve. The quantities are multiplied with the emission factor of the specific plant, quantifying the CO_2 emissions associated with every MWh of power output generated from that plant.

The remaining allowance budget that an agent has at its disposal at time at a certain trading day is divided by the remaining days for which the allowances were issued, in order to calculate a daily budget. This budget is subtracted from the allowance quantity needed for power generation, thus resulting in the bid quantity that an agent submits to the market operator. In consequence, if an agent's budget for the current day is larger than its need for allowances, its bid quantity becomes negative, which corresponds to a selling bid. It is assumed that the market for CO_2 allowances is fully competitive, and the industries outside the electricity sector determine the market price. Generator agents submit price-independent bids, i.e. they are price-takers on the allowance market.

Agents do not act strategically on the market for CO_2 emission allowances – they do not develop bidding strategies through reinforcement learning. However, the costs incurred from allowance prices influence trading strategies on the electricity markets, as specified in the following section.

While optimizing their supply bids, agents consider opportunity costs that they could have achieved on the other market if they had sold their capacity there. Prices for carbon dioxide emission allowances are also included into the reinforcement as opportunity costs. A generator would always have the opportunity to solely sell certificates, thereby realizing a profit. Consequently, he aims at attaining a profit equal to or higher that that which he could have achieved through selling allowances

2.2 Data Input

The simulation model is run with data that approximates the German electricity sector. The system's total electricity demand has been taken from 2006 load data published by the *Union for the Co-Ordination of Transmission of Electricity* (UCTE). Hourly UCTE demand data is published for every third Wednesday of the month. The simulation results represent these days of each month of 2006.

Input data of the power generation mix roughly corresponds to German real-world characteristics. The power plant portfolio is represented in an aggregate way. The four dominant players in the market (E.ON AG, RWE Power AG, Vattenfall Europe AG and EnBW Kraftwerke AG) are represented in more detail, and further players are introduced so that the overall installed capacity and the proportions of different power plant technologies (coal-fired, gas-fired, hydro etc.) are properly represented. Within the power plant portfolio of one generator, all plants using the same fuel or technology are subsumed under one generating unit, and average efficiencies are assumed for these units.

3 Simulation Results

Through simulation runs with the described data input, it should be verified if simulated prices on the day-ahead and on the balancing power market resemble those observed at the real-world markets in Germany (Section 3.1). Furthermore, the impact of emissions trading is analyzed in order to assure that it corresponds to the real-world characteristics (Section 3.2).

3.1 Reproducing Daily Courses of Prices

For the purpose of validating the developed model against real-world data, those days for which the system's total load is known from UCTE data are simulated and resulting prices are compared to EEX and balancing power market prices. As the real-world markets may show extraordinary prices on the specific simulated day, additional average daily courses of prices over all workdays of the same month are calculated and compared to the simulation outcomes. Figures 1-5 display simulation results for runs with Q-learning (simulations ran over 7,300 iterations; the outcome of one run is the average market price over the last 365 iterations. Results are averaged over ten simulation runs with different random number seeds at each run).

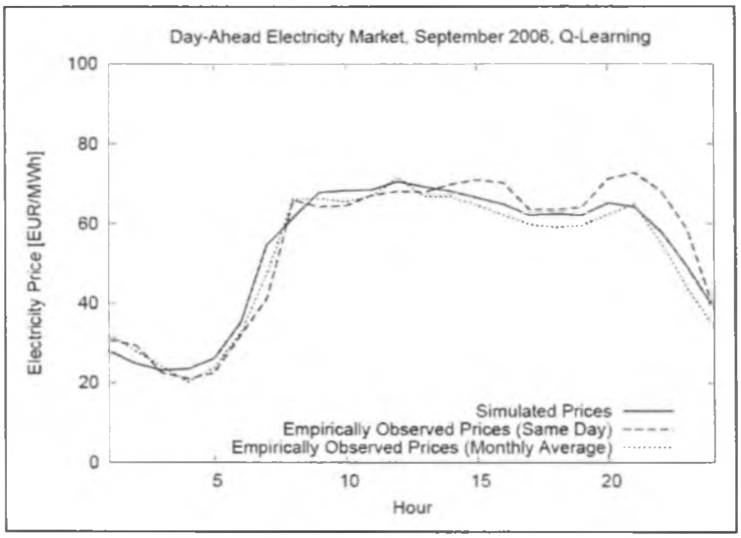

Fig. 1. Simulated and real-world prices on the day-ahead market, September 2006

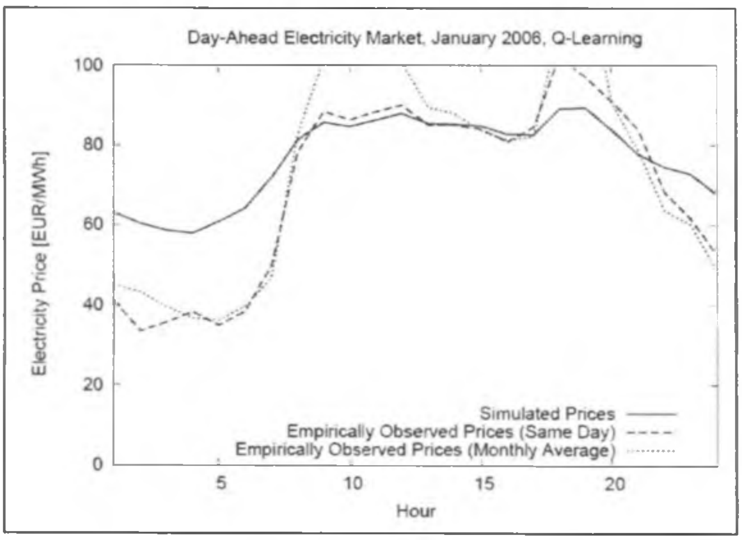

Fig. 2. Simulated and real-world prices on the day-ahead market, January 2006

The continuous lines plot the simulation outcome for the third Wednesdays of every month; the dashed lines plot the empirically observed prices of the same days, and the dotted lines represent average prices over all workdays of the specific months. Figures 1 and 2 display hourly results on the day-ahead market, where empirically observed prices correspond to prices for hourly contracts fixed in the daily *spot auction* operated by the European Energy Exchange AG (Germany's main power exchange).

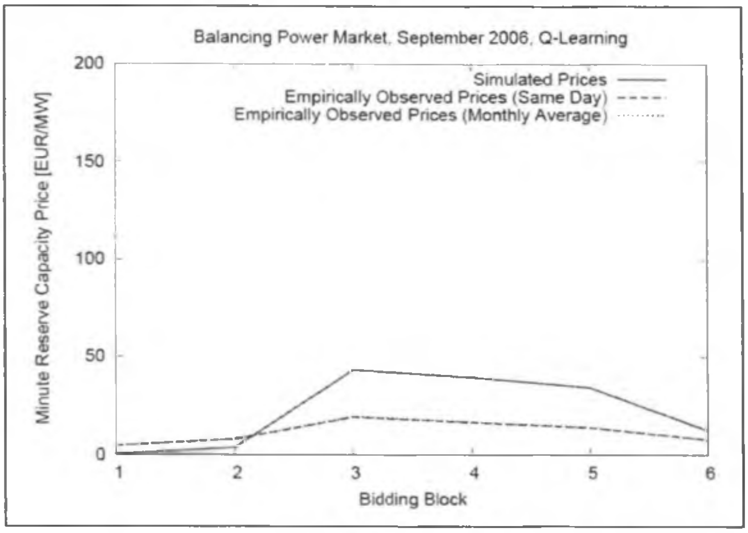

Fig. 3. Simulated and real-world prices on the balancing power market, September 2006

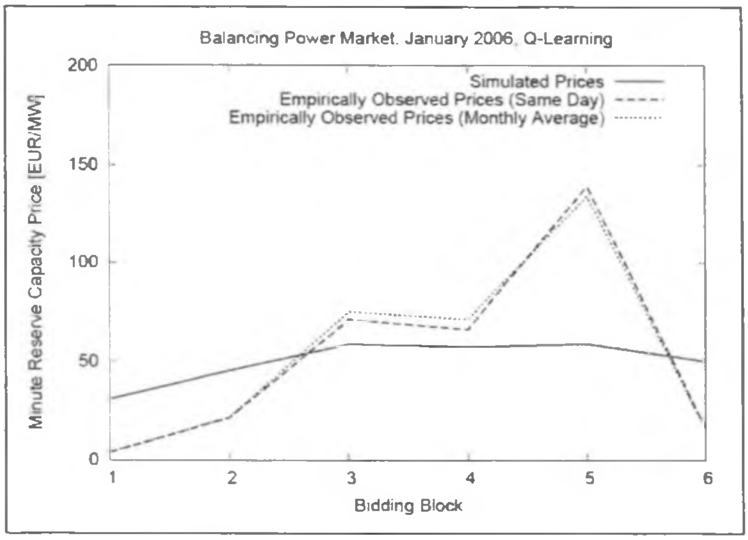

Fig. 4. Simulated and real-world prices on the balancing power market, January 2006

Figures 3 and 4 show results from the simulated balancing power market and the empirically observed prices are averaged over the prices published by the four balancing market operators.

The simulated prices observed on the day-ahead market and on the balancing power market stem from the same simulation run and are a consequence of agents bidding on these two markets (and in addition on the market for CO_2 emission allowances) and optimizing their strategies in face of these market interrelations.

Simulation results for this basic scenario reveal that real-world prices can be reproduced remarkably well for spring, summer and fall months. In winter months, however, simulated prices deviate more strongly from empirically observed prices. In these months of high system load, agents may have more leeway for strategic bidding than has been assumed in the model presented here. Moreover, power plant availability due to maintenance or other planned outages have not been considered here. Although maintenance is mainly carried out during summertime, even small outages may already have a large effect on electricity prices in times when the demand-supply ratio is tight – i.e. during the winter – which may be a reason for the differences between simulation results and real-world electricity prices.

The demand, i.e. the tendered quantity on the balancing power market, is equal for all bidding blocs. This market is cleared first, and the day-ahead market is operated subsequently. As the available supply capacity and the demand quantity in the balancing power market is the same in every hour, differences in prices between the bidding blocs can only result from the inclusion of opportunity costs in the agent's reasoning. The simulation outcome on the balancing power market shows characteristic daily courses of prices, in which capacity prices in bidding blocs 3 and 4 – and 5 in winter months – are considerably higher than those in the nocturnal bidding blocs. Similar characteristics can be observed in the real-world balancing power markets in Germany, although the high prices in the fifth bidding bloc that occur in most winter months can not be reproduced by the simulation model. It is remarkable that the rather low capacity prices in some summer months can be reproduced by the simulation although the possible bid prices that range up to 200 EUR/MWh would theoretically allow much higher prices to occur. This result strengthens confidence in the model validity.

Variability between different runs (i.e. runs with different random number seeds) is very low for simulations with Q-learning. The standard deviation for the resulting prices of the ten repetitions ranges between 0.2 and 2.3 EUR/MWh for different hours on the day-ahead electricity market and between 0.05 and 3.9 EUR/MW for bidding blocks on the balancing power market. With these low variances, one single simulation run already delivers meaningful and reliable results.

In the simulation model, prices are mainly influenced by the demand level, as the principal difference of market conditions in the hours of the considered months is the system's total load. Power plant availability is considered to be constant over the year. This is a simplification which might be altered in future model development. In reality, maintenance of power plants is scheduled discontinuously over the year; around 2% of the total installed generating capacity is off due to maintenance during winter months, and around 10% during summer months [VDN 2004]. In those simulated hours in which day-ahead electricity prices deviate considerably from real-world prices, power plant availability may be an important reason. Besides maintenance, an even more important factor in this context is the available renewable energy production. In the simulation model, renewable energy availability is also assumed to be constant, whereas in reality, water levels of hydroelectric installations and electricity generation from wind energy varies considerably throughout the year and during the day. The high prices in July 2006, which can not be replicated by the simulation model, are also explicable by reduced power plant availability. During the very hot summer in Germany in 2006, it occured that the maximum admissible temperature for rivers was reached and the cooling water flow for thermal power plants had to be reduced as a consequence. Additional drought in many European regions reduced hydro energy availability [EGL 2006]. The combination of these factors, which were not represented in the simulation model, made power prices rise considerably above usual levels in July and, to a lower extent, August 2006.

3.2 Impact of Emissions Trading on Electricity Prices

The data presented in the preceding section corresponds to simulations in which emission allowance trading was integrated – just like in the real-world market of the corresponding time frame. In further simulation runs, it is tested how emissions trading affects prices on the electricity markets. For this purpose, scenarios without CO_2 emissions trading are run and compared to the reference scenario results. The outcome of this comparison is depicted in Figure 5 for the day-ahead electricity market. In order to facilitate the graphical inspection of simulation results, Figure 5 contains resulting prices for all simulated hours of the day-ahead market, i.e. for all 12*24 observations. As prices on the electricity market are strongly influenced by the system's total load (= demand), simulated prices are sorted by load quantities in the corresponding hours. System load is plotted at the second ordinate of the diagrams.

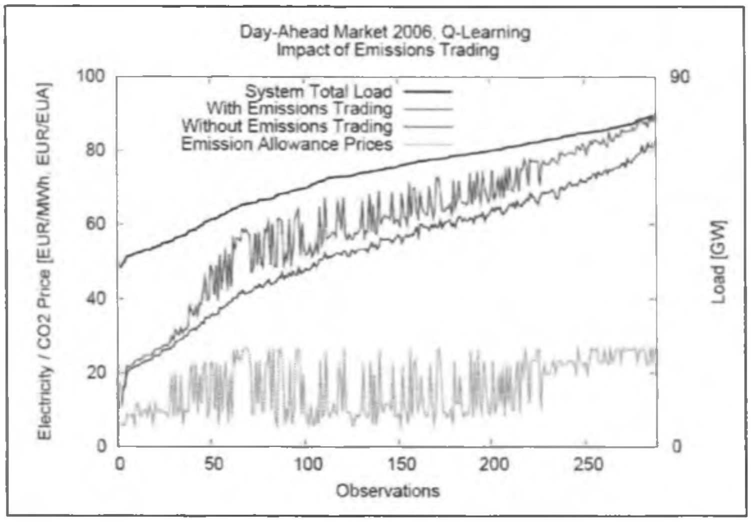

Fig. 5. Impact of CO_2 emissions trading on day-ahead electricity prices

It can be shown that a large fraction of opportunity costs resulting from the possibility of selling CO_2 emission allowances is successfully passed over to electricity market bids, which ultimately raises prices at the day-ahead market and also at the balancing power market. Because of different emission and competition situations in the single hours, the absolute increase in electricity prices is not constant across the simulated hours and bidding blocks.

In hours of low demand, the introduction of emissions trading has hardly any effect on day-ahead electricity prices, because only few power plants that incur high CO_2 emissions are deployed, and supply side competition is strong. In contrast, the difference in prices is considerable in high demand hours, in which many CO_2 intensive power plants are running and competition is weak, so agents can successfully pass over additional opportunity costs to their bid prices. Over a large range of intermediate demand situations, deviations between the scenarios with and without emissions trading fluctuate to some extent. The intuition behind this result is that these hours with similar demand situations belong to different months, and CO_2 prices differ across months. Hours with very high demand all belong to the winter months in which demand is high and consequently many fossil fuel power plants are operated, resulting in (evenly) higher CO_2 allowance prices. This is also illustrated by the green curves that plots prices for CO_2 allowances in Figure %.

As a consequence, it can be concluded that emissions trading considerably influences electricity prices and that it is the main cause for differences in prices resulting for hours with similar demand situations; this is true on both the day-ahead and the balancing power market. Yearly average prices are 13.3 % higher for scenarios with emissions trading on the day-ahead market, and 56.8 % higher on the balancing power market.

4 Conclusions

In this contribution, an agent-based simulation model representing the core features of the German electricity market is presented. The model comprises a day-ahead market for hourly electricity delivery contracts, a procurement market for positive minute reserve and a market for CO_2 emission allowances. Simulated prices from this model are remarkably close to those observed in reality for many months of the year 2006, both on the day-ahead market (compared to EEX prices) and on the balancing power market (compared to the balancing power markets operated in the German electricity sector). Besides, the effect of CO_2 emissions trading on simulated prices is comparable to that observed in the real market, i.e. a large proportion of opportunity costs are successfully passed on to electricity bids, which ultimately raises electricity prices.

The presented model can be used to analyze a variety of possible market structures and market mechanisms with the aim of finding good market designs that take into account market interrelations and other aspects of real-world electricity markets. Analyses of this kind have been conducted by the authors, and additional scenarios are currently developed. For example, the impact of the tendered minute reserve quantity on day-ahead and balancing power market prices is studied in [Weidlich, Veit 2008a] and a variation of the settlement rule as well as the impact of several divestiture scenarios are analysed in [Weidlich, Veit 2008b]. Results from these simulations demonstrate the usefulness of the agent-based simulation model presented here.

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