

Assessing the Effect of Storage Devices and a PHEV Cluster on German Spot Prices by Using Model Predictive and Profit Maximizing Agents

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Abstract—In this paper, the German electricity wholesale market is modeled by individual profit maximizing agents. The agents use a learning approach called “model predictive bidding” to choose bidding curves for the upcoming day which are sent to the spot market. The chosen bidding curves thereby maximize the agents’ expected discounted profits. In contrast to traditional agent learning approaches such as Q-learning or learning classifier systems, the learning approach in this paper is predictive and model based. This predictive approach allows to model storage agents, which anticipate higher and lower future spot prices to charge and discharge their storage. Simulations with different types of storage agents are carried out to assess the impact of those agents on spot prices, price volatility and market-power. The storage agent in one simulation uses a high power output whereas the storage agent in a second simulation has a high storage capacity. Furthermore, a scenario is simulated in which a cluster of PHEVs is simulated as an agent who can be charged or discharged via the electric grid and has a variable charging/discharging power capacity depending on the amount of PHEVs connected to the grid and their current state of charge. In contrast to electric vehicles, PHEVs can drive with either electricity or gasoline. This introduces a higher flexibility in charging/discharging these vehicles. The paper shows that the temporal variable charging/discharging rate of the PHEV cluster results in less market-power by the PHEV cluster compared to a storage device and to a more favorable market output.

Index Terms—Electricity markets, agent-based modeling, multi-agent model, model predictive bidding, German electricity market, wind power, storage devices, PHEV cluster, Vehicle to grid (V2G)

I. INTRODUCTION

THE European electricity industry has undergone substantial changes since the start of the deregulation process in the early 1990’s. The electricity markets moved away from vertically integrated monopolies to liberalized markets [1] [2]. Since the deregulation, the German utility industry faced a consolidation phase which resulted in an oligopolistic market structure where four dominant firms with a combined market share of 90% are apparent [3]. This concentration in electricity production gives potentially rise to gaming and strategic bidding behavior [2]. In addition to the concentration in electricity production, the predictability of future electricity

spot prices might also influence the degree of gaming among the market players. This price predictability is influenced by large scale electricity storage devices since these devices buy electricity when (anticipated) spot prices are low and sell, when prices are high.

In Europe, large scale electricity storage capacities are promoted to handle and integrate a higher amount of renewable energy sources in the future. The EU Renewables Directive and the Green Package 20:20:20 promote renewable energies in Europe and target a 20% share in renewable energy sources by 2020 [4]. The pump-storage hydro power plant Goldisthal in Germany for instance is one of the biggest hydro power plants and has a installed power output of 1’060 MW. The lower and upper water reservoirs are artificially created [5]. More of these artificial types of hydro power plants could be introduced as large scale storage capacity. Clustered Plug-In Hybrid Electric Vehicles (PHEV) as well as electric vehicles being recharged from the electric grid could contribute one other possible technology path in large scale storage. Although they add a load to the electric system, PHEVs promise also advantages to the electric network like the introduction of a large distributed storage [6] [7].

An agent-based model, in which power generating units are modeled as agents, is introduced in this paper to assess the effect of these different types of storage devices on spot prices, bidding behavior and market-power. In particular, it is analyzed if the additional storage capacity gives rise to collusion among the market players by influencing the predictability of future spot prices. The bottom-up modeling approach of agent-based models appears suitable to assess the evolution of electricity prices because agent-based models allow to capture effects related to market-power. Furthermore, the learning algorithm of the agents is predictive and model based to incorporate strategic bidding.

The paper is structured as follows: Section II introduces the basic principles of multi-agent modeling with a special emphasis on electricity markets. Section III specifies the model and discusses the assumptions made. Section V introduces the model predictive bidding learning algorithm. A case study with conventional storage devices is presented in section VI while the PHEV cluster scenarios are illustrated in section VII. Finally, section VIII concludes the paper.

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II. AGENT-BASED MODELING IN ELECTRICITY MARKETS

Agent-based models use autonomous decision-making entities called agents. The agents are characterized by bounded rationality and are able to learn and adapt [8]. Agent-based models put a special emphasis on the interactions of agents to assess their effects on the system as a whole. A key notion is that simple behavioral rules on a micro-level generate complex outcomes on a macro-level [9] [8]. The simulated evolution of the system can be studied both from the perspective of the aggregate population as well as from the individual agent.

The interaction between the agents (power generating units) is complex. The agents are able to learn effects related to repetitive behavior and to incorporate the effect of market-power favorably into their bidding strategies [10] [11]. An oligopoly market is assumed in the following. Thus, electricity producers may bid strategically above their marginal cost as they realize their possible influence on market prices [12].

No assumptions concerning the attainment of an equilibrium are made. There is no guarantee that the aggregated behavior of the system is stable if every agent is trying to maximize its profit. Rather, the actual model execution indicates if an equilibrium is obtained or not [9].

III. SPECIFICATION OF THE MODEL

The objective of the power generating units, which are modeled by agents, is to maximize their expected discounted profits. At day d , the agents send 24 hourly bidding curves for the upcoming day $d + 1$. A bidding curve thereby describes the agent's power output for a given spot price range. The market clearing is then performed for the 24 hours. The implementation of the day-ahead spot market is in accordance with the implemented structure of the major electricity spot markets in Europe where the day-ahead auction market of single hours is the closest to a spot market [13]. In this paper, there is no future, intra-day or balancing market modeled, the work focuses on the day-ahead market.

Each agent is parameterized and described by the following parameters:

- Generation type (nuclear, hard coal, lignite, gas, oil, wind, storage, hydro) of the agent.
- Maximum power output [MW].
- Generator efficiency curve η as a function of the generation technology and output level.
- Generator ramp cost constant δ [€/MW].
- CO_2 emissions per MWh [ton/MWh].
- Technical ramp capacity τ [MW/h].
- Charging efficiency η_{charge} (for storage agents only).
- Discharging efficiency $\eta_{discharge}$ (for storage agents only).
- Maximum storage capacity Φ (for storage agents only).

German exogenous factor and electricity market data for the year 2006 is taken as training data for the agents and the simulations are carried out with German data from the year 2007.

The following simplifications are made:

- There are only generators and consumers in the market, no third party trading intermediaries.

- The grid is modeled as a copper-plate with no congestions and losses.
- The load part of the aggregated demand function is perfectly inelastic. Only the demand of the storage agents leads to an elastic aggregated demand curve.
- The entire volume is traded via the spot market place, i.e. there are no bilateral OTC trades.

IV. COST OF PRODUCTION AND PROFIT CALCULATION

The quantification of the total variable cost $VC_{i,t}^{total}$ for the different generators is a modification of the model proposed by [14] and follows:

$$VC_{i,t}^{total} = VC_{i,t}^p + VC_{i,t}^r + VC_{i,t}^{ea} \quad (1)$$

where $VC_{i,t}^p$ represents the variable production costs, $VC_{i,t}^r$ the ramping and $VC_{i,t}^{ea}$ the emission allowance costs (costs for CO_2 emissions) at time t for generator i . The production costs $VC_{i,t}^p$ comprises specific fuel costs $fc(tech_i, \Lambda_{m,t})$, which depend on agent's generation technology, the daily market price $\Lambda_{m,t}$ of the specific fuel m , the agent's efficiency $\eta(p_{i,t}, tech_i)$ and power output $p_{i,t}$. The efficiency depends on the generation technology and agent i 's power output level at time t . The variable cost of production $VC_{i,t}^p$ can be calculated according to:

$$VC_{i,t}^p = p_{i,t} \cdot \frac{fc(tech_i, \Lambda_{m,t})}{\eta(p_{i,t}, tech_i)} \quad (2)$$

The ramping costs $VC_{i,t}^r$ are calculated by the difference in output level from one hour to the next multiplied by the generator specific ramp cost constant $\delta(tech_i)$:

$$VC_{i,t}^r = (p_{i,t} - p_{i,t-1}) \cdot \delta(tech_i) \quad (3)$$

The emission allowance costs $VC_{i,t}^{ea}$ is determined by a fuel specific constant $\vartheta(fuel_i)$, which defines the CO_2 emissions per MWh fuel burned and the daily price for the emission allowance φ_t . Therefore,

$$VC_{i,t}^{ea} = p_{i,t} \cdot \vartheta(fuel_i) \cdot \varphi_t \cdot \frac{1}{\eta(p_{i,t}, tech_i)} \quad (4)$$

Finally, agent i calculates its profit $\pi_{i,t}$ at time t according to

$$\pi_{i,t} = \lambda_t \cdot p_{i,t} - VC_{i,t}^{total} \quad (5)$$

where λ_t represents the spot price at time t .

V. LEARNING PROCESS OF THE AGENTS: THE METHODOLOGY

The learning methodology incorporates basic concepts of Q-learning (a discussion about Q-learning can be found in [15]). However, instead of deriving the Q-values (expected discounted profits) from trying different actions (bidding curves) in different states, the agents calculate the Q-values directly based on a model. A multi-factor regression model is used to generate spot price predictions, which allow calculating expected discounted profits for every combination of bidding curves.

The learning algorithm is similar to Model Predictive Control in a way that a model generates predictions and the input (bidding curve) for the control horizon is determined such that a given performance criterion (the reward) is maximized. In addition, the learning algorithm follows the concept of a rolling future time horizon for the expected discounted profits optimization.

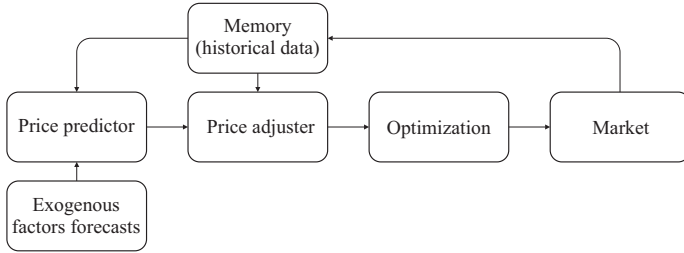


Fig. 1. Flow chart of the learning methodology

Figure 1 illustrates the implemented learning methodology. Each agent predicts future spot prices based on exogenous factor predictions with the price predictor. Additionally, the spot price estimates are adjusted through the price adjuster to incorporate market-power. Based on this information, the agents use dynamic programming as an optimization routine to find the optimal set of bidding curves (an optimal policy), which maximizes the agent's expected discounted profit. The set of bidding curves is then sent to the market where a market clearing takes place. The exogenous variables, spot prices and corresponding bidding curves are saved by each agent in a memory.

A. The price predictor

The agents use an auto regressive multi-factor regression model to create an hourly price forward curve (future spot price predictions $\hat{\lambda}_t$ for hour $t = e, e + 1, \dots, e + k$ where e represents the upcoming day's first hour and k the estimation horizon). The regression model follows

$$\hat{\lambda}_t = \beta_1 \gamma_{t,1} + \beta_2 \gamma_{t,2} + \dots + \beta_N \gamma_{t,N} + \epsilon_t \quad (6)$$

where the estimated spot prices $\hat{\lambda}_t$ are the dependent variables, $\gamma_t = (\gamma_{t,1}, \gamma_{t,2}, \dots, \gamma_{t,N})$ time specific vectors and ϵ_t disturbance terms. The regression coefficients $\beta_1, \beta_2, \dots, \beta_N$ are estimated with data procured by the agent's memory minimizing the sum of squared errors. The following factors are taken into account by the price predictor:

- Lagged spot price values at $\lambda_{t-1}, \lambda_{t-2}, \lambda_{t-3}$. This autoregressive part is added since the time series has significant autocorrelation.
- Dummy variable for Saturday and Sunday.
- Cooling degree day (positive temperature deviation from 18.3°C).

$$cdd_t = \max \{ temp_t - 18.3, 0 \} \quad (7)$$

- Heating degree day (negative temperature deviation from 18.3°C)

$$hdd_t = \max \{ 18.3 - temp_t, 0 \} \quad (8)$$

- Historical price fraction (a historical arithmetic mean of the spot prices for the same hour the last M years)

$$PF_t = \sum_{i=1}^M \frac{\lambda_{t-i \cdot 8760}}{\text{mean}(\lambda_{t-1}, \lambda_{t-2}, \dots, \lambda_{t-M \cdot 8760})} \quad (9)$$

- Current oil price (although this regression coefficient is statistically not different from zero on a 5% significance level it can still be significant in different time periods with high oil prices for instance).
- Wind forecast

The agents thereby use forecasts for the exogenous factors temperature $temp_t$ and wind.

B. The price adjuster

The price adjuster measures the price residuals $\hat{\lambda}_t - \lambda_t$ (the estimated spot price minus the observed price for time t) after every market clearing. Given agent i used bidding curve j in his set of bidding curves a_i at time t , the price adjuster can calculate dynamically the price adjusting value ($pav_i|a_i^j$) for bidding curve j with the reinforcement algorithm:

$$pav_i|a_i^j = \frac{(w \cdot pav_i|a_i^j + (\lambda_t - \hat{\lambda}_t))}{w + 1} \quad (10)$$

where w is a weighting factor. It is thereby assumed that agent i 's set of bidding curves a_i is finite and equal to M . The $pav_i|a_i^j$ value indicates that when agent i used bidding curve a_i^j , the observed spot price λ used to be higher or smaller by the amount of $pav_i|a_i^j$ than the estimated $\hat{\lambda}$ value which is based on exogenous factors. Agent i can use the pav values to adjust the hourly price forward curve to incorporate the effect of his bidding on spot prices. The result is a price prediction matrix which depends on the future time steps $t = e, e + 1, \dots, e + k$ and agent i 's bidding curves $a_i^{1, \dots, M}$.

$$\hat{\lambda}_t|a_i^{1, \dots, M} = \hat{\lambda}_t + pav_i|a_i^{1, \dots, M} \quad (11)$$

C. The optimization routine

The optimization is a mapping of the price prediction matrix to the optimal set of bidding curves μ^1, \dots, μ^N (the optimal policy), which maximizes agent i 's expected total discounted profit over N time steps.

First, the agents calculate their historical estimation error distribution. The historical estimation error for the historical hour t and agent i is defined as $\lambda_t - \hat{\lambda}_t|a_i^{j=f(t)}$, which describes the observed spot price minus the estimated spot price taking into account that agent i used bidding curve j at time t . Based on N historical estimation errors, every agent calculates a historical estimation error probability distribution $pr_i(\Delta\lambda)$. The distribution is different for every agent since the agents incorporate different market-powers (different values for $pav_i|a_i^{1, \dots, M}$). Furthermore, the values for $pr_i(\Delta\lambda)$ are updated after every market outcome.

Two assumptions are made: first, the agents assume that these probabilities do not change when making price forecasts and second, the agents assume that these probabilities are

independent from the price level, the bidding curve, the exogenous factors etc.

With the historical estimation error distributions, agent i can calculate an expected power output $E(p_{i,t}|a_i^h)$ if bidding curve h from agent i 's set of bidding curves a_i at a future time step t is taken. The expected power output $E(p_{i,t}|a_i^h)$ is calculated according to:

$$E(p_{i,t}|a_i^h) = \sum_{\Delta\lambda=-\Delta\lambda_{max}}^{\Delta\lambda_{max}} pr_i(\Delta\lambda) \cdot a_i^h(\Delta\lambda + \hat{\lambda}_t|a_i^h) \quad (12)$$

where $a_i^h(\lambda)$ defines the power output for price λ through agent i 's bidding curve h . Agent i can derive expected power outputs for all M bidding curves a_i^1, \dots, a_i^M and future time steps $t = e, e+1, \dots, e+k$ resulting in an expected power output matrix.

The reward function $g_{i,t}$ corresponds to agent i 's profit at time t and can be calculated with

$$g_{i,t} = E(\hat{\lambda}_{t,c}|a_i^j \cdot p_{i,t}|a_i^j) - (VC_{i,t}^p + VC_{i,t}^r + VC_{i,t}^{ea}) \quad (13)$$

whereby the expected revenue $E(\hat{\lambda}_{t,c}|a_i^j \cdot p_{i,t}|a_i^j)$ is calculated according to:

$$E(\hat{\lambda}_{t,c}|a_i^j \cdot p_{i,t}|a_i^j) = \sum_{\Delta\lambda=-200}^{200} pr_{i,T}(\Delta\lambda) \cdot a_i^j(\Delta\lambda + \hat{\lambda}_{t,c}|a_i^j) \quad (14)$$

In (13), $VC_{i,t}^p$ and $VC_{i,t}^{ea}$ are only functions of $E(p_{i,t}|a_i^{j=f(t)})$ and $VC_{i,t}^r$ depends on the production difference $E(p_{i,t+1}|a_i^{j=f(t+1)})$ and $E(p_{i,t}|a_i^{j=f(t)})$. A simplification is made since it is assumed that $VC_{i,t}^r \ll VC_{i,t}^p$. $VC_{i,t}^r$ is calculated according to

$$VC_{i,t}^r = (E(p_{i,t+1}|a_i^{j=f(t+1)}) - E(p_{i,t}|a_i^{j=f(t)})) \cdot \delta(tech_i) \quad (15)$$

The values for the expected power outputs are defined in the expected power output matrix and values for price predictions in the price prediction matrix. Agent i solves the problem to choose the bidding curves $j = f(t)$ for $t = e, e+1, \dots, e+k$ (the optimal policy) which maximizes his expected discounted profit. This problem can be stated as:

$$V(p_{i,0}) = \max_{(p_{i,t}|a_i^{j=f(t)}, p_{i,t+1}|a_i^{j=f(t+1)})} (\kappa^N g_N(p_{i,N}) + \sum_{t=0}^{N-1} \kappa^t g_t) \quad (16)$$

and is solved using the Bellman equation [16]. With the Bellman equation, the problem can be formulated in a numerical backward induction way as:

$$V(p_{i,t}) = \max (g_t(p_{i,t}, p_{i,t+1}) + \kappa V(p_{i,t+1})) \quad (17)$$

The storage agents use their filling status $f_{i,T} = \int_{t=1}^T p_{i,t} dt$ as state at time T . The filling status is a continuous measure; To apply the DP algorithm, the filling status $f_{i,T}$ is discretized in M discrete levels. A constraint for the storage agent is that

$$f_{i,T} = \int_{t=1}^T p_{i,t} dt \geq 0 \text{ and } f_{i,T} \leq \Phi_i \quad (18)$$

where Φ_i represents agent i 's maximum filling level.

The reward function for the storage agent is divided into two cases: charging and discharging. It follows

$$g_t = -\frac{E(\hat{\lambda}_{t,c}|a_i^j \cdot p_{i,t}|a_i^j)}{\eta_{i,charge}} \approx \frac{\hat{\lambda}_{t,c}|a_i^j \cdot (E(f(i,t)) - E(f(i,t-1)))}{\eta_{i,charge}} \quad (19)$$

for charging (if $E(f(i,t)) \geq E(f(i,t-1))$) and

$$g_t = \eta_{i,discharge} \cdot E(\hat{\lambda}_{t,c}|a_i^j \cdot p_{i,t}|a_i^j) \approx \eta_{i,discharge} \cdot \hat{\lambda}_{t,c}|a_i^j \cdot (E(f(i,t)) - E(f(i,t-1))) \quad (20)$$

for discharging (if $E(f(i,t)) < E(f(i,t-1))$).

For the storage agent, the Bellman equation can be rewritten as

$$V(f_{i,T+1}, f_{i,T} = y) = \max (g_T(f_{i,T+1}, f_{i,T}) + \kappa V(f_{i,T+1})) \quad (21)$$

VI. CASE STUDY 1: THE GERMAN ELECTRICITY MARKET WITH ADDITIONAL STORAGE CAPACITY

In this section, the effect on spot prices of an additional storage device with a high power output of 5 GW and a low electrical energy storage of 57.7 GWh is assessed (5 additional pump-storage power plant such as the one in Goldisthal). This simulation is referred to as *high power* scenario. In a *high energy* scenario, the effect of a storage device with a high electric energy content of 600'000 MWh and a low power output of 2 GW is assessed. The storage agent uses the model predictive bidding scheme in contrast to [17] where only a simplistic price depending charging/discharging approach has been implemented.

A. Spot prices with additional storage capacity

Figure 2 shows the simulated base load prices for the *high power*, the *high energy* as well as the reference scenarios. The price pattern in the *high power* and *high energy* scenarios show a higher cyclical behavior than the *reference* scenario where the base load price rises steadily for about 2 month and drops sharply thereafter. In [18], this price pattern is also observed in an environment with capacity constraints on a transmission line. It is stated that this type of cyclic behavior is related to Edgeworth Cycles. Edgeworth analyzed static Bertrand price equilibriums and showed that there exists generally a cyclic price behavior rather than an equilibrium point when firms face capacity constraints [18].

Table I provides a simulation summary. From a spot price perspective, the additional storage capacity does not help bringing the spot prices to lower levels or considerably decrease the peak/off-peak spread and price volatility. The reason is that gaming activity is increased and Edgeworth price cycles occur.

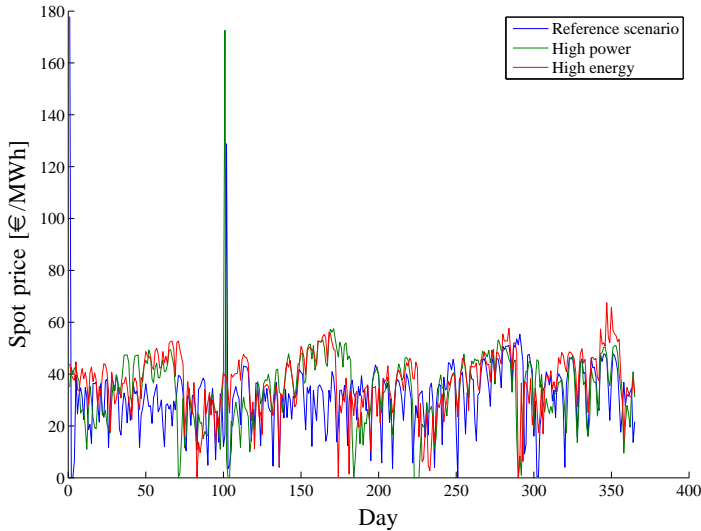


Fig. 2. Base load prices storage and reference scenarios

	Ref. scenario [€/MWh]	High power [€/MWh]	High energy [€/MWh]
Mean base load	36.27	34.28	36.72
Mean peak load	40.50	38.22	39.95
Price std	16.02	16.85	14.74

TABLE I
SUMMARY SPOT PRICES REFERENCE AND STORAGE SCENARIOS

B. Power outputs and market-power with additional storage capacity

Figure 3 shows the power outputs of the different aggregated generation technologies in the *high energy* scenario. Two phases can be distinguished: a price war phase and a relenting phase. In the relenting phase, the nuclear, storage, lignite and hard coal agent produce on a constant level and in the war phase, the nuclear, lignite and hard coal agent are ramping their production heavily.

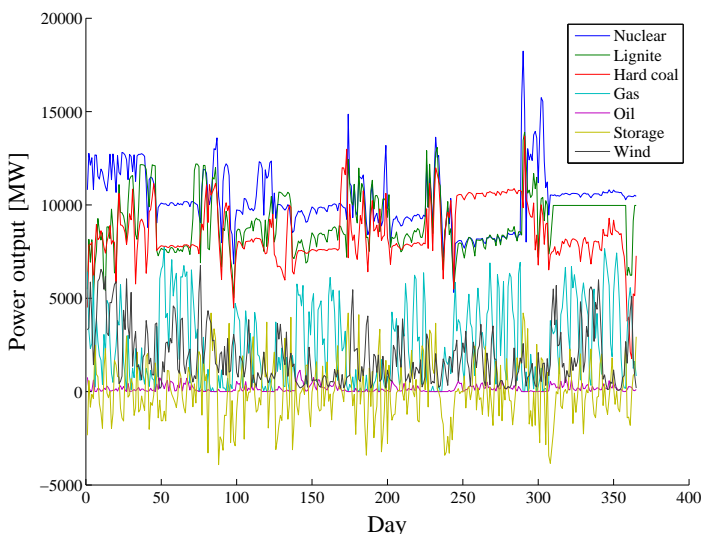


Fig. 3. Power outputs high energy scenario

Figures 2 and 3 show that the raising spot prices in the

relenting phase are caused by collusion among the agents where the same amount of electricity is sold for higher and higher prices. The degree of collusion is increased if the electricity storage capacity and charging/discharging rate of the storage agent is raised because the additional storage device makes the spot prices more predictable. At some level the higher spot prices trigger undercuttings and the price war phase starts.

The time interval for raising prices in the Edgeworth price cycles depends on how fast the regression coefficients are updated. The agents use the trailing 3 month data for calculating the regression coefficients, longer or shorter memory horizons alter the time constant of the price cycles.

VII. CASE STUDY 2: THE GERMAN ELECTRICITY MARKET WITH A PHEV CLUSTER

An aggregation entity as in [19] is assumed which clusters the time-varying battery capacity from plug-in hybrid electric vehicle (PHEV) connected to the electric grid. This aggregation entity buys and sells electric power via the spot market by submitting hourly day-ahead bidding curves to the market and by using the model predictive bidding algorithm.

The available charging/discharging capacity of the PHEV cluster depends on the amount of PHEVs connected to the grid and the state of charge of the PHEVs.

Two simulation scenarios with PHEVs are carried out. In one scenario (the *1 m PHEV* scenario), the cluster consists of 1'000'000 PHEVs (around 2% of the German cars assumed to be PHEVs), whereas in a second scenario (the *8 m PHEV* scenario), the cluster consists of 8'000'000 PHEVs (around 16% of the German cars assumed to be PHEVs).

A. The PHEV cluster model

For modeling the aggregation entity, 84 different drive cycles are assumed for the single PHEVs in the cluster whereby these drive cycles are uniformly distributed among the PHEVs [19].

In contrast to [19], the aggregation entity's electricity spot market purchases and sales have a major impact on the state of charge of the PHEV cluster. The available charging/discharging capacities depend on the fraction of PHEVs connected to the grid, the electricity they use to drive and the historical electricity purchases and sales over the spot market. As a result, the state of charge (soc) of the PHEV cluster can be calculated on a recursive basis:

$$soc(t+1) = soc(t) + \frac{\Delta q_t - dr_t}{Q} \quad (22)$$

where dr_t describes the amount of electricity needed to drive the PHEVs at time t , Δq_t the electricity exchanges over the spot market and Q the maximum storage capacity of the PHEV cluster. The electricity needed to drive the PHEVs follows the formula

$$dr_t = (P_0 - P_t) \cdot v \quad (23)$$

where P_0 is the total number of PHEVs, P_t the number of PHEVs connected to the grid and v a constant which

specifies the amount of electricity a PHEV needs to drive. It is assumed that all PHEVs not connected to the grid travel from one destination to their next one thereby consuming energy. The amount of P_t can be derived from the PHEV fraction connected to the grid.

It is assumed that the maximum storage capacity per PHEV is 12 kWh and that each PHEV connected to the grid is charged with 1.75 kW/PHEV. Hence, the available charging power for the PHEV cluster can be calculated according to

$$\Delta q_{t+1}^{charge} < \frac{P_t}{P_0} \cdot P_0 \cdot 1.75 \text{ kW} \cdot (1 - soc) \quad (24)$$

while

$$\Delta q_{t+1}^{discharge} < \frac{P_t}{P_0} \cdot P_0 \cdot 1.75 \text{ kW} \cdot soc \quad (25)$$

defines the available discharging power. A constraint of the PHEV cluster is that it can not be discharged below 20% of Q .

B. Spot prices with a PHEV cluster

Figure 4 shows the spot prices of the reference, the 1 m PHEV and 8 m PHEV scenarios. Overall, the PHEVs are an additional load since despite the charging/discharging, energy is needed for driving. This explains the higher spot price level in the PHEV scenarios.

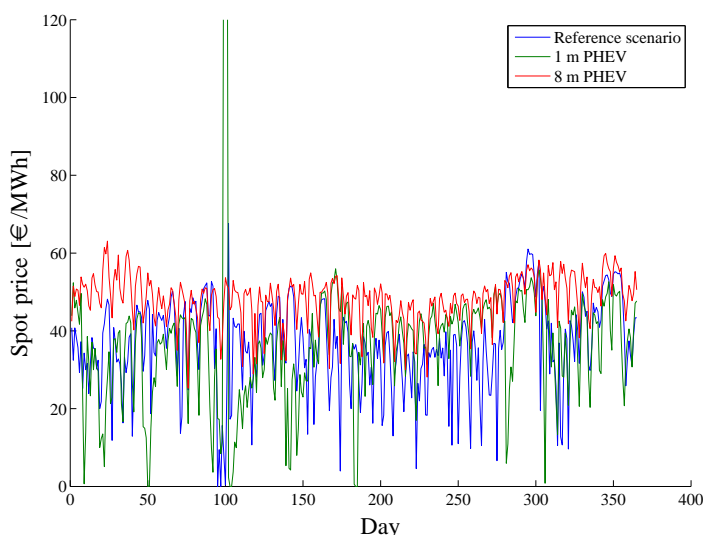


Fig. 4. Base load prices 1 m PHEV, 8 m PHEV and reference scenarios

Table II summarizes the simulations. In the 1 m PHEV scenario, the mean base and peak load prices do not change significantly compared to the reference scenario, but the volatility increases. On the other hand, the mean base load prices rise around 33% in the 8 m PHEV scenario while the peak/off-peak spread is narrowed. The volatility is decreased in the 8 m PHEV scenario.

	Ref. scenario [€/MWh]	1 m PHEV [€/MWh]	8 m PHEV [€/MWh]
Mean base load	36.27	36.53	48.32
Mean peak load	40.50	42.85	50.32
Price std	16.02	22.42	10.12

TABLE II
SUMMARY SPOT PRICES REFERENCE AND PHEV SCENARIOS

C. Power outputs, market-power and profits with a PHEV cluster

Figure 5 shows the power outputs of the agents in the 8 m PHEV scenario. The PHEV cluster allows to use the nuclear, lignite and hard coal power plants very efficiently. They produce on a high and steady level throughout the year which leads to a very low spot price volatility. The PHEV agent allows to provide backup power and stores excess energy if needed. In contrast to the storage scenarios, the PHEV agent results in less predictable spot prices due to the time varying charging/discharging constraints, which in turn decreases the gaming activity and degree of collusion.

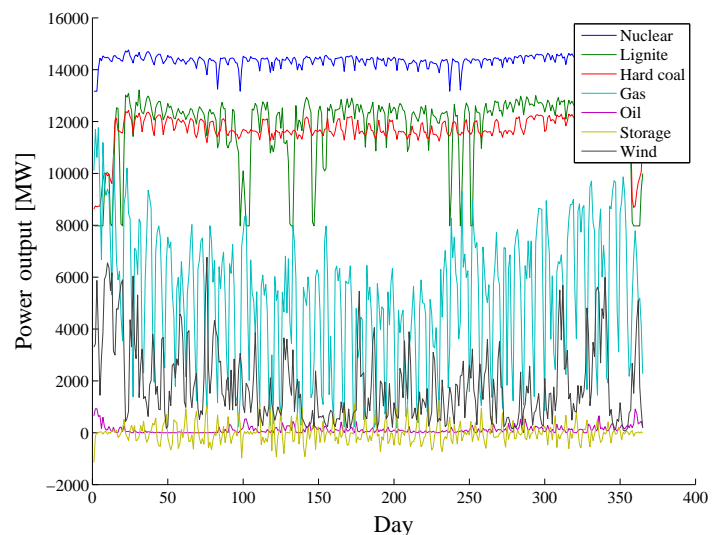


Fig. 5. Power outputs 8 m PHEV scenario

Overall, the total profits for the utilities increase by 116% from the reference scenario to the 8 m PHEV scenario. It can therefore be concluded that the power generating companies have a high incentive to promote the large scale adaption of PHEVs. The PHEV agent attains a profit of roughly 10 million € in the 1 m PHEV and 11 million € in the 8 m PHEV scenario. The reason that the profit in the 8 m PHEV scenario is not higher is due to the much lower spot price volatility. It is remarkable that the profit of the PHEV agent is positive, it implies that people travel using electricity and at the end of the year receive money.

VIII. CONCLUSION

Large scale storage capacity is promoted in Europe to handle the uncertainty in renewable energy production. Storage devices buy electricity when anticipated prices are low and sell, when prices are high. This subsequently leads to a higher

spot price predictability with few extreme spot price outcomes which in turn favors gaming and collusion among market participants. The collusion results in rising spot prices, which at a certain level trigger market players to undercut each other. This behavior is repeated and leads to price cycles. In a well-functioning electricity market though, no agent should be able to significantly alter the spot price by the bidding behavior. Large scale storage capacities therefore do not help to achieve the goal of a well-functioning electricity market.

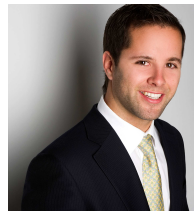
A certain degree of uncertainty in future spot prices is desirable to limit the market-power of the players. Aggregating PHEVs to a cluster and charging/discharging them via the electric grid results in a lower price cycle behavior and hence, allows to use the nuclear, hard coal and lignite power plants very efficiently by providing backup-power and storing excess electricity during night times. The available charging/discharging capacity of the PHEV cluster depends on the amount of PHEVs connected to the grid and their state of charge. This time variability charging/discharging capacity constraints result in less predictable spot prices and as a consequence, in less gaming among the agents.

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