Agent-Based Simulator for the German Electricity Wholesale Market Including Wind Power Generation and Widescale PHEV Adoption

Lukas A. Wehinger, Matthias D. Galus, *Student Member, IEEE,* and Göran Andersson, *Fellow, IEEE*

***Abstract*—An agent-based model is applied to model the German electricity wholesale market with its four major German utility companies. The model is utilized to assess base and peak power spot prices for scenarios implying doubling or tripling wind generation capacity in Germany. Furthermore, the effect of 8 million Plug-In Hybrid Electric Vehicles (PHEVs), incorporating different charging/discharging patterns, on spot prices is evaluated. In the model the power generating units within the utilities are modeled by agents. These agents are trained to increase their profits by using a reinforcement learning approach combined with a genetic algorithm resulting in heuristically optimized bidding strategies.**

This approach allows to take into account strategic market behavior and the exercise of market power when analyzing future wind expansion and wide scale PHEV adoption scenarios. The wind generation is considered as an exogenous input to the model which estimates potential electricity prices and total cost for consumers.

***Index Terms*—Electricity market modeling, agent-based modeling, EEX market, electricity prices, market power, wind power, Plug In Hybrid Electric Vehicles (PHEV), Vehicle to grid (V2G)**

I. Introduction

THE German electricity sector as well as other European electricity markets have undergone substantial changes since the Electricity Market Directive (European Parliament, 1997). The German utility industry faced a consolidation phase since the deregulation and creation of power exchanges [1]. This phase resulted in a market structure where four dominant firms with a combined market share of over 90% are apparent. The concentration of market power in the German utility industry may have resulted in strategic bidding behavior [2]. Agent-based model are capable of capturing market power in such oligopoly market structures.

Additionally, there is a political incentive by the European Union (EU) Renewable Directive 2001/77 and its replacement to promote electricity generation by renewable sources. The Green Package 20:20:20 targets a 20% share of renewable energy sources by 2020 [3]. Wind energy can contribute a major share of this increased renewable energy demand. The increase in wind energy is an exogenous factor that leads to a higher uncertainty in electricity production. This uncertainty can have a major impact on the bidding behavior of the power generators apparent on the market as their ability to predict market prices decreases. The agent-based model is used to quantify the effect of a higher wind energy contribution on spot market prices and volatility.

The EU's energy policy further addresses the transportation sector, requiring a mandatory limit of 120 grams of CO_2/km for new cars by 2012 to curb the greenhouse gas emissions [4]. One possible technology path to achieve this is represented by Plug-In Hybrid Electric Vehicles (PHEV), being recharged from the electricity grid [5]. Although adding load to the electricity system, PHEVs promise also advantages to the electricity network like the introduction of a large distributed storage [6]–[9]. This will alter again the bidding behavior of power generators. Hence, the PHEVs are introduced in the agent-based model and are considered as a storage device which is being charged when electricity prices are low and feeding energy back to the grid when the prices are high. The model allows then to analyze the effect of different PHEV charging scenarios on spot prices and price volatility.

The paper is structured as follows. Section II introduces the basic principles of multi-agent modeling and in particular the Learning Classifier System (LCS). Section III shows the application of the agent-based model for an electricity market. A case study with a high wind energy contribution is presented in section IV while PHEVs scenarios are illustrated in section V. Finally, section VI concludes the paper.

II. Agent-Based Modeling and Learning Algorithm

Multi-agent modeling allows to analyze the interdependencies of the micro-level (participants) and the macro-level (the overall market structure). The effects related to repetitive behavior and learning of market participants with special emphasis on market power can be incorporated in these models [4], [10]. Individual agents are characterized by bounded rationality, using heuristic or simple decision rules and may be able to learn, adapt and replicate [11], [12].

One way of modeling the learning process by the agents is the use of Learning Classifier Systems (LCS). These systems are machine learning systems which acquire a collection of simple production rules, called *classifiers*. LCS is able to interact with an arbitrary environment using an input interface with detectors. Each detector contains information about one attribute of the environmental state. The output interface are the actions undertaken [13].

These systems solve *classifying problems* as well as *reinforcement problems* by evolving a set of rules. An LCS

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is adaptive in the sense that its ability to choose the best action improves with experience. Reward received for a given action alters the likelihood of taking that action in the same circumstance in the future [14].

For solving the reinforcement problem, LCS is using the Q-learning algorithm where agent i is learning which reward p (reward prediction) he can expect if he choses action $a_{i,t}$ given the environmental input set $s_{i,t}$ at time t. After the game is played and the rewards r_i have been observed, agent i updates its reward prediction function p_i according to the following expression in 1 where $\alpha_{i,t} \in [0,1]$ is the degree of correction.

$$p_i(a_{i,t}, s_{i,t}) \leftarrow p_i(a_{i,t}, s_{i,t}) + \alpha_{i,t}(r_i - p_i(a_{i,t}, s_{i,t})) \quad (1)$$

The agents are using an ϵ-Greedy policy in choosing an action for a given input set $s_{i,t}$. The action with the highest expected payoff is chosen with the probability $1-\epsilon$ and a random action otherwise.

In addition, LCS is using a genetic algorithm for enhancing the agent's classifier population. The genetic algorithm uses operations such as classifier selection, reproduction, mutation and recombination to create new classifiers. These offspring classifiers are derived from strong classifiers already existing in the classifier population [15].

The agents in this paper are using a modified XCS classifier system including several extensions to LCS [15], [16]. It differs from LCS in the following aspects:

- The most important difference between XCS and LCS is the introduction of fitness. In classical LCS, only the reward prediction is calculated for choosing a classifier by the ϵ-Greedy policy. XCS introduces a new parameter called "accuracy", based on which the fitness of a classifier is calculated. This fitness is used to weight the reward prediction. Therefore, not only the predicted classifier reward is important, but also the accuracy by which this reward can be estimated.
- The genetic algorithm for classifier reproduction applies only on the basis of the environmental input match (match set). With this implementation, reproduction favors classifiers that are frequently active (part of an action set) whereas the classifier deletion is performed in the whole classifier population [17]. In classical LCS methodology the genetic algorithm is applied to the whole classifier population.
- The population of classifiers is of maximum size. Excess classifiers are deleted with a probability proportional to the action set size estimate that the classifier occurred in. This ensures that there is always a sufficient number of classifiers in the action sets for arbitrary environmental input [17]. In contrast, LCS deletes classifiers with a low reward prediction.

III. Modeling an Electricity Market with LCS Methodology

In contrast to perfectly competitive markets where participants are assumed to be price takers and prices are equal to marginal costs of supply, an oligopolistic electricity market assumes that electricity producers may bid strategically above their marginal costs realizing their possible influence on market prices [18]. The objective of the power generating units, which are modeled by agents, is to maximize their own as well as the profit of their corresponding utility. The electricity generation technologies nuclear, lignite, hard coal, gas, oil and wind energy are differentiated. Different bidding strategies are tested and optimized by the agents.

The agents receive an exogenous binary input string, which consists of the following sensor inputs s, describing the environment:

- Week-end vs. week-day
- Quarter of the year
- Hour
- Hourly day-ahead wind forecast
- Temperature deviation of a 10-day moving average
- Fuel market price

Additionally, the agents store their past production levels and add them to the sensor input s. This information is important mostly for the nuclear, but also for the lignite and hard coal power plants because they suffer from high ramping cost and low technical ramping rates. As a consequence, they are trying to keep production at a constant level to reduce ramping cost.

A fixed feed-in tariff is paid to the wind producers. Their production is subtracted from the total demand. The other generators (agents) are receiving a day-ahead wind forecast for every hour. For simulating the wind energy production, the real wind energy data is taken.

The calculation of the total variable cost $VC_{i,t}^{total}$ for every agent is crucial to the model. Equation (2) presents a modification of the proposed model by [19] and its components are explained below.

$$VC_{i,t}^{total} = VC_{i,t}^{P} + VC_{i,t}^{R} + VC_{i,t}^{EA} + VC_{i,t}^{CS} + VC_{i,t}^{EnS} \quad (2)$$

The term VC^R represents the ramping cost, which is calculated by the difference in output level from one hour $P_{i,t}$ to the next hour multiplied by a generator specific ramp cost constant δ_{tech_i}.

$$VC_{i,t}^{R} = (P_{i,t} - P_{i,t-1}) \cdot \delta_{tech_i} \quad (3)$$

The emission allowance accounts by $VC_{i,t}^{EA}$. Its calculation takes into account a fuel specific constant λ_{fuel_i} specifying the number of tons CO_2 emissions per MWh fuel burned and the daily price for the emission allowance φ_t in price per ton CO_2 produced.

$$VC_{i,t}^{EA} = P_{i,t} \cdot \lambda_{fuel_i} \cdot \varphi_t \cdot \frac{1}{\eta_{P_{i,t},tech_i}} \quad (4)$$

The cost for a cold start, denoted by $VC_{i,t}^{CS}$, occurs if a power plant shuts down its production for a certain time and takes it online afterward. The cost for the cold start is modeled by (5), where ϑ_{tech_i} represents the start-up cost of a fully cooled down power plant. The value T_{tech_i} is a characteristic time constant of the generator and t_{hour} counts the number of hours the power plant has been shut down.

$$VC_{i,t}^{CS} = \vartheta_{tech_i} \cdot \left(1 - e^{-\left(t_{hour}/T_{tech_i}\right)}\right) \quad (5)$$

Finally, $VC_{i,t}^{EnS}$ accounts for the technical ramping limits of the generator. If a power plant needs to ramp to an extent it is technically not capable of, it has to pay for the energy not served or the excess energy it feeds into the grid with a constant markup. The costs depend on the technical ramping limits ς_{tech_i} per hour by the generator and the market clearing price MCP_t and are calculated by equation (7)

$$\begin{aligned} &\text{if } |(P_{i,t} - P_{i,t-1})| > \varsigma_{tech_i} \\ &\quad VC_{i,t}^{EnS} = 1.3 \cdot (|(P_{i,t} - P_{i,t-1})| - \varsigma_{tech_i}) \cdot MCP_t \quad (6) \\ &\text{else} \\ &\quad VC_{i,t}^{EnS} = 0 \end{aligned}$$

The reward $r \in R$ is defined by the profit of the generator and by the profit of the utility to which the agent belongs. Equation (7) computes the profit $(\pi_{i,t})$ for each agent. Formula (8) computes the profit $(\Pi_{j,t})$ for the corresponding utility j at time t.

$$\pi_{i,t} = MCP_t \cdot P_{i,t} - VC_{i,t}^{total} \quad (7)$$

$$\Pi_{j,t} = \sum_{i=1}^{N(j)} \left(MCP_t \cdot P_{i,t} - VC_{i,t}^{total}\right) \quad (8)$$

The profit of each agent and utility is used by the reinforcement learning algorithm as a feedback variable to update the prediction and fitness of the classifiers used in the corresponding bidding round.

IV. Case Study 1: The German Electricity Market with higher Wind Energy Contribution

The specified agent-based model is applied to the German electricity market which is one of the largest in Europe with a total net consumption of ca. 530 TWh and total installed net generating capacity of 116 GW in the year 2000 [20].

A. Spot Prices with Additional Wind

In a first step, the agent-based model is used to simulate base and peak load prices under reference conditions. Several years are calculated to analyze the ability of the generators to adapt their bidding behavior in order to increase their own as well as the reward of the corresponding utility. The utilities E.ON, EnBW, RWE, Vattenfall and others are considered. Each of the electricity generation agents belongs to one of the five utilities. The year 2008 serves as basis year for the simulation. After the calibration under reference condition, three different wind scenarios are analyzed by changing the amount of wind energy capacity.

The installed wind energy capacity in Germany in 2008 amounted to 23.6 GW. In the first two scenarios the amount of wind energy is doubled and tripled compared to the reference scenario. In the third scenario, the total amount of nuclear electric energy per year is replaced by wind energy. This results in an installed wind power capacity of 114 GW. The presented results are drawn after five years of simulation time, in which the agents had time to adapt to the new environment. Figure 1 shows the spot market prices for the different scenarios.

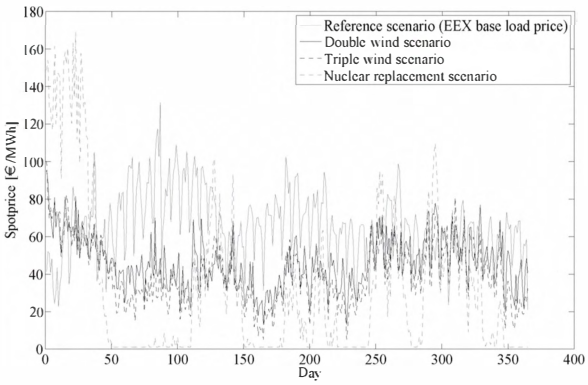

Fig. 1. Simulated base load prices for different wind scenarios

For the double and triple wind scenarios the spot market prices are lower as compared to the reference scenario. This is mainly due to the fact that the wind energy is subtracted from the auctioned amount of demand, since a fixed feed-in tariff is paid for the wind energy.

The nuclear replacement scenario shows a high price volatility. The simulated prices are bounded by zero €/MWh. Negative prices would occur without a boundary. The prices are high during times with low wind power contribution because the coal, gas and oil fired power plants have to replace the nuclear ones.

B. Total Cost for Consumers with Additional Wind

Figure 2 shows the total cost for the consumer. The cost for the double, triple and reference scenarios are close together. Obviously, the wind energy needs to be subtracted from the total load. The generated wind energy is paid the fixed feed-in tariff. If this energy had been produced with another generation technology and the spot market price had been in the same order of magnitude as the feed-in tariff, the total cost for the end consumer would not have changed significantly. The average EEX base load spot market price in 2008 was €65.76 and the fixed feed-in tariff was set to €75 per MWh in 2008, which are both in the same order of magnitude. The price level of the spot market and the feed-in tariff are therefore crucial to the outcome of the total cost for the consumers. The electricity spot price levels observed at the EEX were high in 2008, in other years with a lower spot price level the difference in total cost for consumers between these scenarios is higher.

The electricity cost for the end consumer shows a very different pattern in the nuclear replacement scenario. The cost are often higher than in the other scenarios especially during times with low wind energy contribution. Here, the wind power can change dramatically between two subsequent hours and the remaining power plants are not capable of ramping their production fast enough. More gas fired power plants, which are expensive, have to be put online to cover this spread.

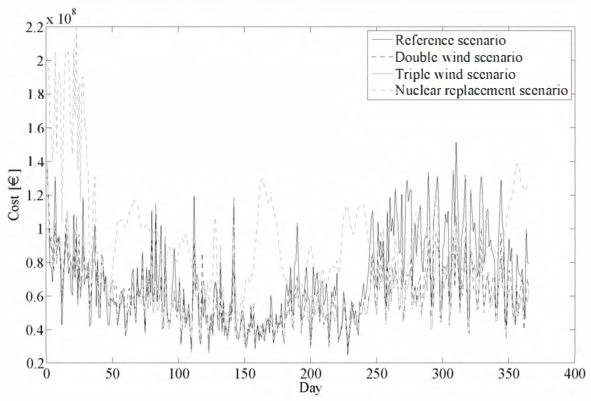

Fig. 2. Total electricity cost for the end consumer for different wind scenarios

V. Case Study 2: The German Electricity Market with PHEVs

Plug-In Hybrid Electric Vehicles (PHEVs) are proposed as near term technology and a transitional step to electric vehicles potentially achieving a sustainable transportation sector. They include an electric motor as a primary and an internal combustion engine (ICE) as a secondary energy source. PHEVs recharge their batteries via the electric grid while using their ICE only as an ancillary power source [21]. The vehicles could provide the potential to flatten the load curve through intelligent recharging routines as well as providing a large distributed storage to the electricity system. Several cases are modeled in this paper with respect to PHEVs to analyze their behavior on spot prices.

A. Charging PHEVs with a Given Loading Distribution

In a first modeling approach, it is assumed that the PHEVs are charged by a given charging distribution. In [22] a charging distribution for PHEVs is proposed. A slightly modified distribution is used in this paper to assess the effect on spot market prices by charging PHEVs according to this distribution. The PHEVs are charged between 4 pm and 9 am with a peak PHEV charging between 11 pm and 4 am. Except for the evening peak, the vehicles are charged during off-peak hours. The PHEVs are assumed to be fully charged within one hour although it is likely that PHEVs would charge longer since they would be typically connected to the low voltage grid. There, the recharging power can be small [23].

Further, it is assumed that there are eight million PHEVs. The daily distance d_{day} traveled by the PHEVs is lognormaly distributed with a mean of 50 km and a standard deviation of 40 km. The average energy rate k_{avg} of the vehicles corresponds to 0.2 kWh/km according to [24]. The electricity demand E_{PHEV} for the hour h by the PHEVs in [kWh] can be computed according to (9), where $D(h)$ is the distribution value from the charging distribution at hour h.

$$E_{PHEV} = 8 \cdot 10^6 \cdot d_{day} \cdot k_{avg} \cdot D(h) \tag{9}$$

Figure 3 shows the simulated base and peak load spot market prices and the 2008 EEX spot prices. It shows that the simulated prices and observed EEX prices deviate more during the winter month and are closer together during the summer. The reason for this phenomenon is found in the merit order of the electricity producer bidding curves. The aggregated spot market supply curve is much steeper for higher output quantities. Therefore, the additional load of the PHEV increases spot prices more in the winter when the load is in general higher than in the summer.

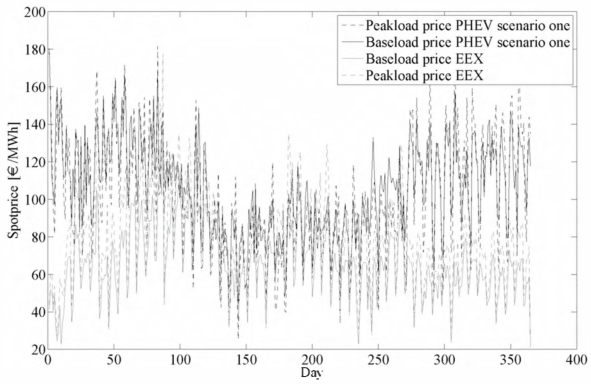

Fig. 3. Base and peak load prices in 2008, charging PHEVs with a given loading distribution

Table I provides a simulation summary. Surprisingly the simulated base load prices are higher than the peak load prices. This shows that PHEVs, which are mainly charged during off-peak hours, dramatically increase the off-peak demand. A higher off-peak demand would flatten the daily load curve and decrease the hourly price volatility, but the simulation shows that the standard deviation of the simulated prices is higher than the observed one. The reason for that is the assumption that PHEVs are recharged within an hour. Significant additional power demand occurs during the peak charging times of PHEV around midnight. As a consequence, the daily load pattern would have an additional demand peak during midnight beside the one at noon and the one in the evening.

	Simulated prices [€]	Observed EEX prices [€]
Mean base load price	105.58	65.78
Mean peak load price	102.11	79.44
Std. deviation base load	24.87	18.14
Std. deviation peak load	30.96	24.27

TABLE I
SIMULATION SUMMARY, CHARGING PHEVS WITH A GIVEN LOADING DISTRIBUTION

B. Charging PHEVs During Off-Peak Hours

Ref. [25] suggests that the PHEVs could be charged during the night hours to shape the load curve toward a more flattened shape. The main difference to the previous scenario is that all PHEVs are charged after 9 pm. Additionally, the maximum charging capacity per vehicle is set to 1400 W.

Figure 4 shows the spot market prices for the scenario where all PHEVs are charged during off-peak hours. The price level differences between the observed EEX prices and the simulated prices are again higher during the winter month. Compared to the previous PHEV charging scenario the general price level is remarkable lower. The total amount of energy

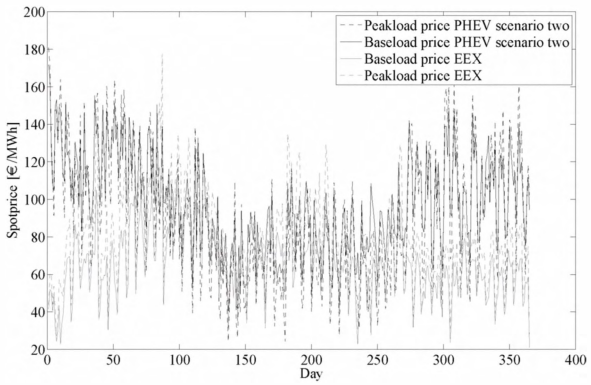

Fig. 4. Base and peak load prices in 2008, charging PHEVs during off-peak hours

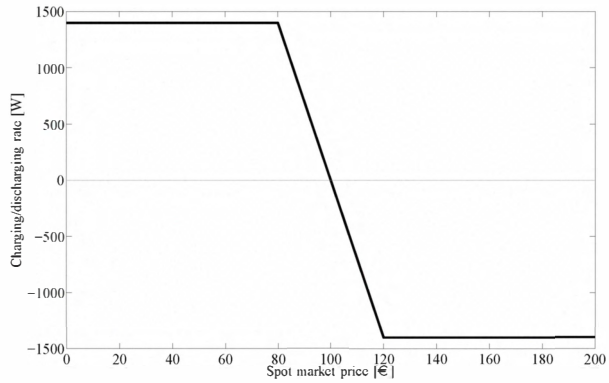

Fig. 5. Spot market price depending charging

demanded stays the same, so the timing of PHEV charging has a major impact on spot market prices.

The analysis of the simulated profits of the utilities under this PHEV scenario shows that all utilities achieve higher profits compared to the scenario without PHEVs. These are a result of a generally higher demand on one hand and a more flattened daily load pattern on the other hand. The flattened demand allows the utilities to run the lignite and hard coal power plants at higher output levels. The gas turbines have to be turned on less frequently and in general the ramping costs are decreased substantially. It can be assumed that utilities have an incentive to promote PHEVs since they allow to use the power plants more efficiently and generate higher profits.

C. Introducing Plug-ins with Spot Market Price Sensitive Charging/Discharging Characteristic

In this scenario, price dependent charging is modeled. The PHEVs are able to feed energy back to the electric grid during periods with high price levels. Figure 5 shows the charging of the PHEVs as a function of the spot market price at $t-1$. A similar approach is suggested in [26]. The curve is characterized by four parameters: The maximum charging power, the maximum discharging power, the threshold price at which the charging starts to decrease and the switching point where the charging is equal to zero. It is assumed that all the PHEVs are connected to the grid between 5 pm and 8 am. The maximal charging and discharging rate is set to 1400 W. The threshold price is equal to €80 and the switching point €100. A constraint to the problem is that the PHEVs cannot be discharged to a level lower than the one they were initially connected with.

Figure 6 shows the spot market prices for the simulation setting with a price sensitive charging/discharging. It illustrates that the price fluctuation is lower compared to the other scenarios. The price level often stays within a band between €100 and €120.

It can be seen that the price level is rather high in this scenario. The simulation output of the spot market prices depends crucially on the chosen price threshold and switching point. The PHEVs buy and sell electricity around the switching point, pushing market prices above and below the switching point from one hour to the other. This reduces the lifetime

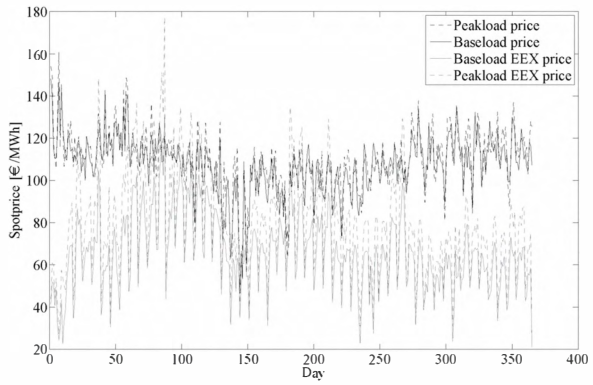

Fig. 6. Base and peak load prices in 2008, price sensitive charging/discharging

of the batteries and artificially increases trading volumes. The price oscillates around the switching point.

The prices are locked in at the switching point, even if excess generation capacity would be available and generation cost would be substantially lower than the spot prices. The agents are able to act strategically and exercise market power since the price depending charging of the PHEVs makes the load more predictable and results in a feed-back system.

VI. Conclusion

Agent-based models can provide insights into pricing, gaming and strategic behavior in imperfect markets such as electricity where the single actors act within bounded rationality.

Here, the application of the agent-based market model shows that an increase in stochastic uncertainty of power production by doubling or tripling the installed wind power does not substantially change the costs for electricity consumers. However, the simulation has been done for a year with a high price level. During years with lower price levels the difference in the cost for the consumers could increase. Replacing the fixed feed-in tariff with a market-driven/market-based instrument could at least help to decrease the spot price volatility since it is often cheaper to shut down wind power plants than ramp coal or even nuclear power plants. Replacing nuclear power plants with wind energy increases the spot price volatility as well as the cost level for the consumer.

Furthermore, widescale PHEV integration with a given charging distribution or off-peak charging increases spot price volatility and price levels especially during the winter time, even though the PHEVs flatten the hourly electricity demand. Using a simple price depending charging scheme, that gives PHEVs the ability to discharge the batteries during high price levels, reduces spot price volatility. However, the resulting price levels are highly dependent on the chosen switching price between charging and discharging of the PHEVs since the scheme results in a closed loop system that locks prices in at the chosen switching price. Generators learn to anticipate the effect of the increased electricity demand below the switching point and are able to increase their market power by restricting power output below the switching price. The price dependent charging could be replaced by a more advanced algorithm in order to bring the spot prices to lower levels.

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