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Effects of electric vehicle charging strategies on the German power system

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HIGHLIGHTS

- A broad range of CO_2 prices was assumed in order to gain robust results.
- EVs can exacerbate or mitigate peak load depending on the charging strategy.
- Different CO_2 prices lead to different qualitative impacts on power plant dispatches.
- Taking Germany's neighboring countries into account, the system benefits from V2G.
- Charging with V2G does not necessarily lead to higher CO_2 emissions.

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ABSTRACT

We analyze the impact of different electric vehicle (EV) charging strategies on the German power system in the year 2030 by explicitly including neighboring countries. A novel parametrization approach dealing with the weekday dependent variations of EV demand is introduced. Investigating a broad interval of CO_2 prices yields robustness against varying merit order curves. The underlying nonlinear relationship leads to qualitatively different impacts of EVs on power plant dispatch at different CO_2 prices. Furthermore, we find that curtailment of renewable energy sources is reduced independently of the charging strategy. Concerning system cost and emissions, the charging strategy vehicle-to-grid proves to be most beneficial. We show that at low CO_2 prices, a production increase of emission intense technologies, such as lignite power plants is overcompensated by several other system components.

1. Introduction

Charged with electricity from low carbon sources, electric vehicles (EVs) are capable of reducing CO_2 emissions in the transportation sector. Apart from reducing operational CO_2 emissions, EVs will impact the power system depending on the charging strategy. These strategies can be classified according to the degree of intelligent system integration. With uncontrolled charging (UNC), users charge as soon as they are connected to the grid. In the case of cost driven charging (DSM) - a special form of demand-side management - there exists a fixed point in time when charging should be completed. Consequently, charging can be controlled - often through price spreads - within the resulting time interval. If there is also the opportunity to feed electricity back into the grid, price spreads have the potential to be still further exploited. This is referred to as vehicle-to-grid (V2G), a concept which was first made popular by Kempton and Tomić [1].

In previous studies, different authors have implemented EVs into power systems which affect either prices or demand directly. For a small distribution network, Morais et al. show that intelligent charging offers the flexibility for smoothing the load curve [2]. Kristoffersen et al. [3] analyze DSM charging behavior for the Danish power market as price-takers and if there is market power. In the first case, charging takes place during nighttime, whereas with market power it is partly conducted during daytime. Moreover, a potential reduction of system cost by flexible DSM charging compared to less sophisticated charging strategies is analyzed in [4–6]. A reason for this is found in the shifting of a large fraction of EVs' demand to hours characterized by lowest steady state operational cost and a small fraction to cut-off ramping cost [6]. Weis et al. conclude that this advantage is even higher in cases where additional wind generation has to be integrated, and increases

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when it prevents capacity expansion [7]. Otherwise, system operation cost can be reduced by a substitution of thermal plants through RES [8,9]. Hedegaard et al. see a substantial reason for operational cost reduction in the reduced need for peak load power plants [10]. Under the condition that the dispatched wind energy does not exceed the required charging energy by a large margin, EVs also help to circumvent imbalance cost from wind [11]. Talebizadeh et al. [12] and Li et al. [13] also find a further reduction of system cost through the integration of V2G. Withthin the Nordic power system, which is already characterized by large amounts of (hydro) storage capacity, Graabak et al. [14] reveal only minor impacts of EVs. Eventually, the highest flexibility results from additional provision of spinning reserve. According to Pavić et al. [15], in combination with DSM this is even more valuable than V2G without spinning reserve.

In terms of CO_2 emissions, literature is ambiguous. On the one hand, controlled charging lowers CO_2 emissions due to a decreased number of start-ups and part load operation hours [16]. This also holds if the share of RES can be significantly increased through V2G [9]. According to the authors in [17], emission saving through better RES integration overcompensates for additional emissions from marginal electricity generation. On the other hand, load shifting to hours with lowest power prices might increase emissions [18,19,13]. This contradiction is emphasized by Hedegaard et al., who state that effects of EVs vary highly from country to country [10].

On the smallest time scale, EVs are suited to contribute to frequency response [20]. The authors in [21] argue that for such system services electric delivery trucks are most profitable, since they have a larger battery and are dispatched in a more rational way.

In the following, we study the impact of the three EV charging strategies on the German power system.[1] This case holds relevance because it constitutes a large-scale power system undergoing a deep structural transformation towards RES, coined the "Energiewende". Moreover, EVs offer demand and storage flexibilities which are currently quite scarce in Germany. Hence, this case is also of interest for other power systems aiming to significantly increase their share of RES, and which are currently mainly characterized by thermal generation accompanied by only minor storage capacities.

We contribute to the existing literature in the following ways. We use sophisticated and unfolded EV data to represent distinct units of EV clusters. Weekdays and weekend days are grouped consistently with daily varying power system demand. Furthermore, we offer an option to deal with the respective independence of these day types existing in traffic studies. Compared to [19,23], we expand the German case by its neighboring countries, taking into account interdependencies with other power systems. Since these effects are nonlinear, different system states might lead to different conclusions. In particular, we show that the effect of EVs on different power plant types differs qualitatively with different CO_2 prices. Therefore, we generalize the impact of EVs given different shapes of the merit order curve caused by a detailed set of varying CO_2 prices.

The remainder is organized as follows. In Section 2, the implementation of EVs into a unit commitment (UC) model is formulated. Section 3 provides the parametrization for the underlying European power system for the year 2030 and the parametrization of the EV clusters in Germany. Section 4 comprises simulation results regarding system operation cost and CO_2 emissions, as well as a detailed analysis of interacting different power production facilities and the power trade balance of the German power system. The results and limitations are discussed in Section 5 with respect to the modeling approach and the chosen parametrization. Finally, Section 6 concludes. Appendix A comprises the nomenclature. Appendix B contains a schematic representation of the model MICOES. The EVs' data and further figures associated with the sensitivity analysis are presented in Appendices C and D.

[1] Although intuitively it seems that UNC is not viable with a large share of EVs, there is detailed work by Harris and Weber [22] that suggests otherwise.

2. Methodology

EVs are implemented in the spot market UC model MICOES. Therein, different generation facilities are represented by their techno-economic characteristics. The objective is to minimize the system's operation cost, as schematically given by Eq. (1). Since power plant production $sup_{t,i}$ is semi-continuous, binary variables $su_{t,i}$ are used to model start-up processes for each unit i and time step t. The associated variable and start-up costs are C_i^{var} and C_i^{su}, respectively.

$$\min \sum_t \sum_i \{ C_i^{var} \cdot sup_{t,i} + C_i^{su} \cdot su_{t,i} \} \qquad (1)$$

The objective is subject to system (electricity and heat balance) and unit constraints (such as ramp rates, minimum load or shut down times). RES feed-in is based on synthetically generated time series for all countries related to the weather conditions of one reference year. To account for the overall energy balance, curtailment of RES is feasible. In congruence to the current market conditions, this curtailment is priced. Energy transfer between the countries is restricted through net transfer capacities (NTCs). A detailed model description of MICOES can be found in [24]. A graphical overview is given in Appendix B.

In this paper, we focus on the modeling of EVs and their corresponding parametrization.

2.1. Modeling electric vehicles

EVs are implemented according to the three charging strategies of UNC, DSM and V2G. The reference case without any EVs is denoted by NoEV. Due to its deterministic character, the UNC case is modeled via adding the EVs' demand to the system's electric energy demand. In contrast, DSM and V2G are considered as small mobile energy storage plants, accounting for additional degrees of freedom to the power system. The switching options between charging and discharging as well as the state of the connection to the grid are represented by a mixed integer programming formulation. Instead of choosing the available fleet formulation applied by [6,12,16], EV clusters with distinct arrival and departure times are used in order to circumvent energy transfer between vehicles with different driving patterns.

In lieu of optimizing the entire year at once, the rolling horizon approach was used as demonstrated in Fig. 1, in order to reduce computational complexity. A reduction to a sequence of subproblems seems to be more suitable, since it better accounts for uncertainty over longer time periods.[2] In each iteration, one optimization is carried out over an optimization horizon (OH) comprising T hours. The control horizon (CH) then acts as a 'memory' keeping track of the system's state.[3]

Fig. 2 displays the modeling scheme of the mobile storage implementation for one storage entity i. The chosen optimization horizon covers more than one day, enabling the mobile storage plants to optimize their charging over night while anticipating lower spot market prices.

The corresponding equations are discussed below, with

[2] The optimization covers an entire year. Note that weather predictions are already very unreliable over a few days.

[3] In the applications reported in this work, we chose: scheduling horizon = 1 year, OH = 36 h, CH = 24 h.