

Article

Simulating Electric Vehicle Diffusion and Charging Activities in France and Germany †

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Abstract: Plug-in electric vehicles (PEV) are considered to reduce oil dependency, noise, and local air pollution as well as greenhouse gas emissions caused by road transportation. Today, the early market penetration phase has started and can be observed in many countries. But how could the diffusion and adoption of PEV be modeled to create consistent scenarios? With which PEV driving and charging behavior can these scenarios be associated and what load-shifting potentials can be derived? This work provides an answer to these questions by describing a hybrid modeling approach of a PEV diffusion scenario consisting of a top-down macro-econometric Bass model, answering the question as to at what point in time how many PEV will be on the market, and a bottom-up micro-econometric binary logistic PEV adoption model answering who is likely to adopt. This set of methods is applied to representative mobility data sets available for France and Germany in order to simulate driving and charging behaviors of potential French and German PEV adopters. In addition, a sampling method is presented, which reduces computational times while intending to remain representative of the population of PEV adopters considered. This approach enables the consideration of PEV at a detailed level in an agent-based energy system model focusing on European day-ahead markets. Results show that PEV diffusion dynamics are slightly higher in France than in Germany. Furthermore, average plug-in times, average active charging periods, average load-shifting potentials, and average energy charged per PEV differ slightly between France and Germany. Computational times can be reduced by our approach, resulting in the ability to better integrate PEV diffusion, adoption, and representative charging demand in bottom-up energy system models that simulate European wholesale electricity markets.

Keywords: technology diffusion; PEV (plug-in electric vehicle); Germany; France; smart charging

1. Introduction

Greenhouse gas (GHG) emissions have a significant impact on the climate, leading to many undesirable side effects [1]. In Europe, this realization led to an agreement on long-term targets for the reduction of GHG emissions: by 2050, these should be reduced by 80% compared to 1990 levels [2]. The share of the transport sector in European GHG emissions was 24% in 2016 [3]. Moreover, fossil fuels are finite resources which are predominantly being imported. Against the background of a growing share of emissions in the transport sector [4], emission reduction strategies within this sector could be particularly effective [5]. Current political efforts to reduce GHG emissions in the transport sector are scarce compared to the societal adaptations necessary to achieve significant reductions [6]. In the global context, it is assumed that emissions in the transport sector could double

due to the rising energy demand in emerging countries [7]. This applies in particular to motorized private transport. Cars are responsible for around 12% of the total European Union emissions of carbon dioxide [8]. A promising strategy to reduce GHG emissions in the transport sector is the electrification of cars [6,8,9], especially with increasing penetration of renewable power production [10,11]. In industrialized countries in particular, the number of plug-in electric vehicle (PEV) registrations has been rising continuously since 2008 [12] despite barriers specific to PEV, such as limitations in range, a lack of charging infrastructure, and high purchase prices [13]. PEV describe vehicles that can charge their battery from external energy sources and comprise plug-in hybrid and pure battery-electric vehicles.

For the estimation of potential structural and economic effects of PEV diffusion, for example, on charging infrastructure, power supply, or power prices, adequate PEV diffusion models are necessary, showing at which point in time how many PEV are being charged at which locations, and how much energy they need to be charged. Energy-system models often aggregate PEV-specific loads due to the computational effort needed for modelling driving and charging patterns in detail [11,14]. According to Richardson (2013) a balance between computational ease and real-world accuracy must be found [14]. Therefore, this work answers the following research question:

How is it possible to combine the modeling of PEV adoption, charging behavior, and load-shifting potentials in energy-system analysis for France and Germany?

In the following, we provide a hybrid PEV diffusion and adoption model, based on reliable demographic data, that can be applied in complex and granular simulation environments. Moreover, we present a re-sampling method to drastically reduce the computational costs of running the model in high-penetration scenarios. Our approach considers PEV on a detailed level in an agent-based energy system model simulating developments of and within European day-ahead electricity markets [15].

After Section 2 describes related work, Section 3 explains the methods and data used. Section 4 and Section 5 present and discuss the results for the original and re-sampled case. Section 5 concludes and gives an outlook for future research.

2. Related Work

As our work deals with three subtopics, we structure the following section accordingly. First, we show recent research on market penetration studies and user acceptance. Second, we address more specifically the combination of bottom-up and top-down approaches in this field. Finally, we focus on PEV charging and customer preferences.

Literature on the diffusion of PEV is a broad research field which has been evolving considerably over the last decade. Reviews exist for methods used to model the market penetration of PEV [16,17]. The review by Gnann et al. (2018) [18] focuses on international PEV market diffusion models and compares corresponding research questions, assumptions, and results to find that there are country-specific differences in the importance of input factors. Coffman, Bernstein and Wee (2016) [19] provide a review on factors affecting PEV adoption. They show that the public charging infrastructure is an important factor associated with PEV uptake. In addition, they identify that actual purchases are much lower than consumers' stated preferences derived from studies primarily relying on surveys about hypothetical situations. Rezvani, Jansson and Bodin [20] review consumer PEV adoption studies presenting a comprehensive overview of the drivers for and barriers against consumer adoption of plug-in PEVs. Kühl et al. (2019) [21] analyze German Twitter data and literature on customer needs concerning e-mobility. Price-related needs and needs concerning car characteristics are overrepresented in literature. On the other hand, charging-related needs are particularly overrepresented in the Twitter data set.

Combining bottom-up and top-down approaches in models for vehicle diffusion and adoption has become more popular in recent years [16,22–24]. Not only personal preferences influence adoption decisions, but also macro-economic parameters. In particular, better designs of interfaces between models and surveys could lead to an improvement of PEV penetration models [17], which

is, for example, addressed by Wolinetz and Axsen (2017) [25]. Disaggregated survey data facilitate forecasts of potential future market developments already in early market phases [16] and enable the analysis of effects of varying input parameters on market developments [25]. PEV penetration models based on aggregated data, on the other hand, are suitable for medium- to long-term forecasts, as long as sufficient market development data is available [16].

The stream of research on PEV and infrastructure is extensive. Hardman et al. (2018) [26] provide a review of consumer preferences of and interactions with charging infrastructure. They show that the most important location for PEV charging is at home, followed by work, and then public locations. Gnann and Plötz (2015) [27] provide a review of combined models for market diffusion of alternative fuel vehicles and their refueling infrastructure. They find that simulation is the most common approach for interaction models. Richardson (2013) [14] reviews the current literature on PEVs, the electric grid, and renewable energy integration, discusses key methods and assumptions, and reviews the economic, environmental, and grid impacts of PEVs. He further shows that PEVs can significantly reduce the amount of excess renewable energy produced in an electric system. García-Villalobos et al. (2014) [28] present a review of different strategies, algorithms, and methods to implement smart charging control systems and identify significant projects around the world about PEV integration. Habib, Kamran, and Rashid (2015) [29] review vehicle-to-grid (V2G) technology and various PEV charging strategies, and analyze their impacts on power distribution networks. Mwasilu et al. (2014) [30] review smart metering and communication infrastructures and identify strategies for integrating PEVs into the electric grid. Hu et al. (2016) [31] present a review and classification of methods for smart PEV charging for fleet operators.

Focusing on users' charging preferences in particular, Chen et al. (2019) [32] propose a multi-objective scheduling method for PEV charging events. Korkas et al. (2018) [33] present an adaptive learning-based approach for nearly optimal dynamic charging of PEV fleets respecting user preferences. Simulation results demonstrate a robust behavior of the approach respecting stochastic arrival and departure times of PEV, different pricing models and solar energy production. Clairand et al. (2018) [34] analyze effects of an aggregator's smart charging approach under consideration of users' preferences. The aggregator allows PEV charging at the lowest cost while complying with technical constraints required by distribution system and transmission system operators. In addition, PEV users can choose among different products that meet their needs in terms of charging time. Case study results show that savings between 5% and 50% compared to the direct charging scenario can be realized.

In conclusion, the majority of research handles one aspect of PEV diffusion, adoption, or charging behavior at a time. In the following, we combine established modeling methods in a hybrid approach to make possible the comprehensive and integrated simulation of PEV market developments while ensuring sufficient granularity of individual mobility needs. In this way, we can incorporate behavioral aspects of PEV use within an energy system model that focuses on coupled day-ahead wholesale electricity markets in Europe. Modelling PEV charging activities in a bottom-up way, i.e., on the basis of individual parking and charging events, permits the analysis of emergent effects of different charging strategies on aggregated PEV demand profiles and corresponding effects on day-ahead market prices and CO₂ emissions. In addition, despite the high PEV-specific granularity, the approach presented in this study intends to keep simulations feasible in terms of calculation costs, while maintaining a good approximation of reality at the same time.

3. Method: A Hybrid Modelling Approach

To find adequate answers to the research question, Section 3.1. describes the hybrid PEV diffusion approach applied. This includes a model variant intending to reduce computational effort, in order to support the integration of PEV in holistic energy system modeling. Section 3.2 describes the method deriving the corresponding PEV charging behavior of the PEV adopters and key metrics for the consecutive analysis.

3.1. Plug-In Electric Vehicle (PEV) Diffusion and Adoption

This section shows the development and interactions of a granular hybrid model for PEV uptake and use in Europe. Section 3.1.1 describes our application of the top-down macro-econometric Bass diffusion model, Section 3.1.2 deals with a bottom-up micro-econometric binary logistic PEV adoption model, and Section 3.1.3 discusses how these models interact and considers a model variant reducing computational effort.

3.1.1. Bass Diffusion Model

The Bass diffusion model is used to model PEV diffusion in the market areas under consideration [35]. In this model, innovation diffusion depends on the interaction between current and potential adopters, called innovators and imitators. These are represented by an innovation coefficient (p) and an imitation coefficient (q). M is the market potential, and t the index for the year considered. The model produces diffusion values for every year $t - t_0$ since the start year t_0 which must satisfy $t - t_0 = 0$ at model initialization. The number of cumulative adoptions up to time t , $N(t)$, is represented by Equation (1):

$$N(t) = M \frac{1 - e^{-(p+q)(t-t_0)}}{1 + \frac{q}{p} e^{-(p+q)(t-t_0)}} \quad (1)$$

Taking into account annual PEV stock numbers, assumptions about medium-term governmental targets and the premise that there will be a complete substitution of internal combustion engine vehicles in the long run (which already reflects the targets of some European governments, such as France, not to register petrol and diesel vehicles after 2040 [36]), equation parameters for the innovation and imitation coefficients are determined. However, in the long term, autonomous driving and car sharing might result in smaller vehicle fleets. Due to the challenges that internal combustion engine vehicles impose on society, it can be assumed that in the future, environmental standards will be further tightened. PEV are likely to be the first choice for meeting these fleet standards in the mid-term, as suggested by growing investments in the expansion of charging points and the upcoming portfolios of major vehicle manufacturers, even if alternative technology paths could be taken (for example, fuel cell technology). A non-linear regression method is used to determine the parameters of the Bass PEV diffusion scenarios for France and Germany (Equation (1)). Levenberg-Marquardt's numerical optimization algorithm [37,38] is used for non-linear curve fitting using OriginPro 2017G.

3.1.2. Binary Logistic PEV Adoption Model

In addition to knowing how many PEV will be registered at a given time (Section 3.1.1), car companies and grid operators are interested in receiving an answer to the question as to which customers will shift first to PEV. Consequently, private purchase intentions for PEV by German and French users of commercial PEV were analyzed within the accompanying research activities of the project *Cross-border Mobility for Electric Vehicles (CROME)* [39]. As the survey was carried out directly after the employer had decided to participate in the project, many of the respondents had only little experience with PEV. The conducted online survey included a question as to whether the German and French PEV users of commercial and public enterprises could imagine buying a PEV privately in the next 10 years [40,41]. In addition, the respondents were asked for further information on their mobility behavior, the role of the respondents in their companies, their experiences with PEV, household income, car-use frequency, nationality, and the number of cars in households in order to examine whether the data on future PEV purchase decisions can be explained by these variables. Dependencies between PEV adoption intentions and these variables are observable and can be described with a binary logistic regression model [41].

3.1.3. Hybrid PEV Diffusion Modeling Approach

Representative mobility studies are available for France and Germany [42,43]. We assume that individuals using cars currently will also be using cars in the future and will eventually become PEV users at a certain point in time. PEV adoption probabilities $p_i^{PEV\ adoption}$ are calculated (Section 3.1.2) and assigned to every car-driving individual $a_i \in I$ within each of the representative mobility studies [42,43] as described in [44]. The car-driving individuals have an individual weight w_i depicting their representativeness of true car-driving individuals, and are sorted by $p_i^{PEV\ adoption}$ to obtain a sorted list of car users $I^{sort} = \{a_i \in I: p_1^{PEV\ adoption} \geq p_2^{PEV\ adoption} \geq \dots \geq p_i^{PEV\ adoption}\}$. $A_{\tilde{t}}^{Adopter\ set} \subseteq I$ represents the set of PEV-adopting individuals in a country in a certain year \tilde{t} .

We use two different approaches to determine the set of PEV adopters ($A_{\tilde{t}}^{Adopter\ set}$ and $\hat{A}_{\tilde{t}}^{Adopter\ set}$) in a specific year \tilde{t} . The traditional approach uses Method 1 and has already been applied by Ensslen et al. 2014 and 2018 [44,45]:

Pseudocode of Method 1

```

1  for all  $\tilde{t}$  do
2      while  $a_i \in I^{sort} \wedge W \leq N(\tilde{t})$ 
3          Set  $W = W + w_i$ 
4          Add  $a_i$  to  $A_{\tilde{t}}^{Adopter\ set}$ 
5      end while
6  end for

```

According to the approach described with the pseudocode of Method 1, all car users $a_i \in I^{sort}$ become PEV adopters $a_i \in A_{\tilde{t}}^{Adopter\ set}$ if their PEV adoption probability $p_i^{PEV\ adoption}$ is sufficiently high for the year \tilde{t} and if their combined weight W does not exceed the total number $N(\tilde{t})$ of PEV adopters for that year.

As computing times of our heuristic PEV charging algorithm [45] scale linearly with the number of adopters and corresponding charging events, which in turn grow exponentially with the growth of initial purchases [35], we use an alternative approach described in the pseudocode of Method 2. This limits the number of adopters to k^{limit} as well as their charging events, but still intends to be representative of the original PEV-adopting population $A_{\tilde{t}}^{Adopter\ set}$ identified with Method 1.

Pseudocode of Method 2

```

1  for all  $\tilde{t}$  do
2      Set  $\hat{I}_{\tilde{t}}^{sort} = \{I^{sort} \mid i \bmod z_{\tilde{t}} = 0\}$       with  $z_{\tilde{t}} = \text{nint}\left(\frac{W_{\tilde{t}}^{Adopter\ set}}{k^{limit}}\right)$ 
3      while  $a_i \in \hat{I}_{\tilde{t}}^{sort} \wedge \hat{i} \leq k^{limit}$ 
4          Set  $\hat{Q}_{\hat{A}_{\tilde{t}}^{Adopter\ set}} = \hat{Q}_{\hat{A}_{\tilde{t}}^{Adopter\ set}} + q_i$ 
5          Add  $a_i$  to  $\hat{A}_{\tilde{t}}^{Adopter\ set}$ 
6      end while
7      while  $a_i \in \hat{A}_{\tilde{t}}^{Adopter\ set}$ 
8          Set  $\hat{w}_i = w_i \cdot \eta_{\tilde{t}}^{scaling}$       with  $\eta_{\tilde{t}}^{scaling} = \frac{Q_{\hat{A}_{\tilde{t}}^{Adopter\ set}}}{Q_{\hat{A}_{\tilde{t}}^{Adopter\ set}}}$ 
9      end while
10 end for

```

Method 2 first calculates $z_{\tilde{t}}$ in order to define a reduced sorted list of PEV drivers $\hat{I}_{\tilde{t}}^{sort}$ for every year \tilde{t} (line 2). The reduced adopter set $\hat{A}_{\tilde{t}}^{Adopter\ set}$ is a limited, sorted selection of every $z_{\tilde{t}}$ th PEV adopter from I^{sort} of size k^{limit} (line 5). The daily charging energy demand q_i specific to adopter a_i is accumulated to $\hat{Q}_{\hat{A}_{\tilde{t}}^{Adopter\ set}}$ (line 4) and set in relation to the total daily charging energy demand of the original adopter set $Q_{\hat{A}_{\tilde{t}}^{Adopter\ set}}$, producing the scaling factor $\eta_{\tilde{t}}^{scaling}$ for that year \tilde{t} . The scaling factor is applied to the original weight w_i for each adopter a_i in the reduced set in order to account for the reduced sample size (line 8). Scaling to total energy demand instead of adopter weight is essential as the goal of the simulation is to assess the adopters' impact on an energy system.

3.2. PEV Charging

The persons adopting PEV in the representative French and German mobility studies are assigned mobility profiles specific to a reference date. We assume that the mobility patterns of car use remain constant as long as the range of the PEV is sufficient for the trip lengths. If the pure electric range is not sufficient, we assume that the PEV are equipped with small combustion engines, so-called range extenders. We assume the same car-use behavior on every day of the simulation and a 1:1 relation between PEV adopters and PEV. As vehicles are parked at home or at the workplace most of the time [20], load-shifting potentials are highest at these locations. Therefore, we assume that PEV adopters have the possibility to charge their cars at home and at work. Combining driving and parking profiles with assumptions on PEV energy consumption, battery capacity, and available charging power allows us to determine the energy requirement and the load-shifting potential of each charging process [44–46].

A charging event x (Figure 1) can be described as follows: After arriving at a charging station at time $t_x^{arrival}$ with an energy charging level of $CL_x^{arrival}$ (in kWh), the PEV is directly charged up to an energy content determined by individual minimum range (MR) requirements CL_x^{MR} . Starting from this point in time (t_x^{CC}), charging event-specific load-shifting potentials Δt_x^{LSP} provided by PEV users can be used by service providers (so-called aggregators) for flexible controlled charging (CC). At the point in time of departure $t_x^{departure}$, the charging level is at $CL_x^{departure}$.

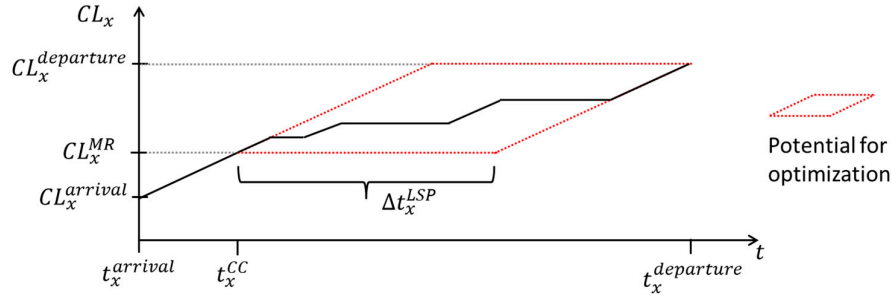


Figure 1. Plug-in electric vehicle (PEV) charging event x with load-shifting potentials.

Plug-in times Δt_x^{plug} specific to charging event x are calculated by subtracting arrival time from departure time (Equation (2)).

$$\Delta t_x^{plug} = t_x^{departure} - t_x^{arrival} \quad (2)$$

Active charging times Δt_x^{active} are determined by dividing the energy charged ($CL_x^{departure} - CL_x^{arrival}$) by the maximum charging power P_x^{max} of a charging event (Equation (3)).

$$\Delta t_x^{active} = \frac{CL_x^{departure} - CL_x^{arrival}}{P_x^{max}} \quad (3)$$

Load-shifting potentials Δt_x^{LSP} are calculated by subtracting active charging times Δt_x^{active} from plug-in times (Equation (4)).

$$\Delta t_x^{LSP} = \Delta t_x^{plug} - \Delta t_x^{active} \quad (4)$$

Total energy charged E^{total} is calculated by adding the energy charged of the single charging events (Equation (5)).

$$E^{total} = \sum_{x \in X} (CL_x^{departure} - CL_x^{arrival}) \quad (5)$$

Total energy directly charged E^{direct} is calculated by adding the energy directly charged of the single charging events x , depending on the availability of load-shifting potentials (Equation (6)). In case load-shifting potentials are available ($1_{[\Delta t_x^{LSP} > 0]}$), the vehicle charges up to the minimum range. If there is no potential ($1_{[\Delta t_x^{LSP} \leq 0]}$), the vehicle charges directly and as much as possible before departure.

$$E^{direct} = \sum_{x \in X} \text{Max}\{CL_x^{MR} - CL_x^{arrival}, 0\} \cdot 1_{[\Delta t_x^{LSP} > 0]} + \sum_{x \in X} (CL_x^{departure} - CL_x^{arrival}) \cdot 1_{[\Delta t_x^{LSP} \leq 0]} \quad (6)$$

Total energy flexibly charged (controlled charging) E^{flex} is calculated by subtracting E^{direct} from E^{total} (Equation (7)).

$$E^{flex} = E^{total} - E^{direct} \quad (7)$$

4. Results

Section 4.1 describes the PEV diffusion scenarios developed for the French and German markets while Section 4.2 presents the simulation results of PEV charging. Section 4.3 shows the effects of the applied re-sampling method (Method 2) on the results compared to the original results.

4.1. PEV Diffusion and Adoption

The Bass diffusion models used to project the future PEV stock are estimated based on the data presented in Table 1.

Table 1. Data and parameters used for diffusion model estimation.

PEV Stock	France	Germany
End 2009	-	3032
End 2010	3368	4404
End 2011	6167	8670
End 2012	12,805	13,582
End 2013	22,217 [47]	23,208 [48]
End 2014	33,595	36,175
End 2015	54,282	48,688
End 2016	79,856	54,997
Mid 2017 [1]	101,799	92,731
Expectation 2030	6,000,000 [49]	6,000,000 [50]
Total vehicle stock (M) *	32,675,972 [47]	45,803,560 [48]

* Please consider that new developments in the context of car sharing and autonomous vehicles might result in an overall lower future vehicle stock.

The expectations of six million PEV in 2030 by French public authorities [49] are in line with the government targets set in Germany [50]. These expectations are taken into account in the scenario calculations resulting in the parameters for the Bass diffusion model shown in Table 2.

These two PEV diffusion scenarios are rather optimistic. The innovation coefficient (p) of the French PEV diffusion scenario is considerably higher than that of the German scenario (cf. Table 2). However, imitation coefficients (q) are on a similar level. According to Figure 2, the models' forecasts of PEV stock are well below the original national policy targets in France (2 mn in 2020 and 4.5 mn in 2025, [51]) and Germany (1 mn [50]).

Based on historical new registrations for 39 countries, innovation and imitation coefficients of Bass diffusion models have been estimated by [52] (France: $p = 1 \times 10^{-4}$ and $q = 0.4$; Germany: $p = 2.5 \times 10^{-5}$ and $q = 0.5$). The innovation coefficients for Germany and France in our results are somewhat higher (France: $p = 1.44 \times 10^{-4}$; Germany $p = 4.31 \times 10^{-5}$), but relatively low in comparison to other common innovation coefficients averaging $p = 0.03$ [52,53]. The estimated imitation coefficients are slightly below the average of $q = 0.38$ [52,53] (France: $q = 0.31$; Germany: $q = 0.32$), but are comparable with other innovations [53]. Differences could be due to the fact that only sales figures of zero-emission PEV were included in [52], but all types of plug-in PEV are considered in our study.

Table 2. Bass diffusion model parameter estimates.

Parameter	France		Germany	
	Mean	Std. Dev.	Mean	Std. Dev.
p	4.31×10^{-5}	2.67×10^{-5}	1.44×10^{-4}	1.82×10^{-5}
q	0.32	0.004	0.31	0.0015
t_0	2008.22	5.82	2010.01	1.05
R^2	~1		~1	

To answer the question of who adopts PEV in France and Germany, we identify persons adopting PEV in representative mobility data sets [42,43]. The mobility studies *Mobilität in Deutschland (MiD 2008)* and the *Enquête nationale transports et déplacements (ENTD 2008)* contain information on mobility behavior as well as on the households surveyed, the individuals living there, their distances traveled, and corresponding vehicles used.

PEV adoption probabilities are assigned to the persons interviewed in the national mobility studies using the binary logistic PEV adoption model as described in Section 3.1. The higher the probability of PEV adoption, the sooner these persons are assumed to adopt PEV.

The two different methods (Methods 1 and 2) are subsequently applied in order to obtain the original and the reduced PEV adopter samples. Exemplary results are shown in Figure 2. Method 2 significantly reduces the samples that represent EV adopters, for example, down to 20% of the original number for the case of France in 2030.

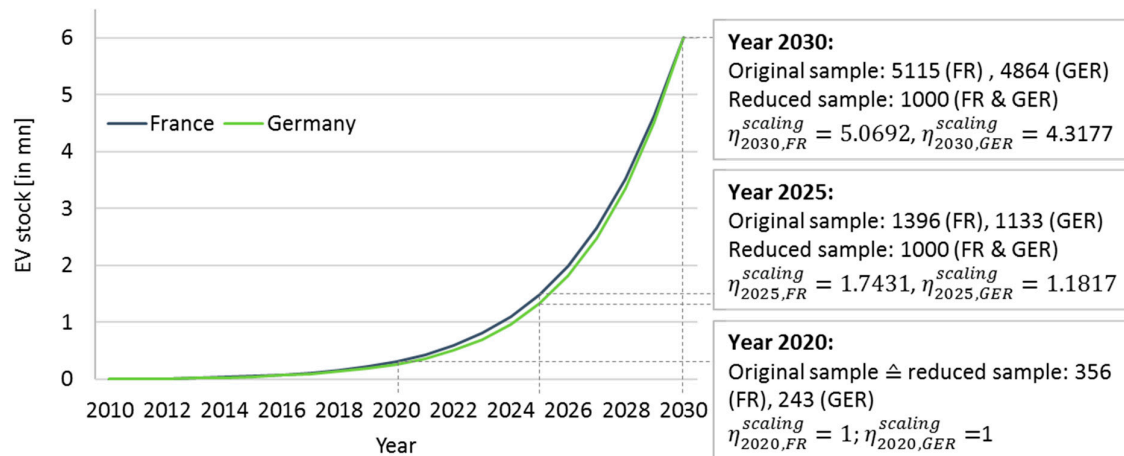


Figure 2. PEV diffusion scenarios for France and Germany.

4.2. PEV Charging

For simulation of the charging behavior, we assume that PEV are charged at home and at work. Information on the charging behavior and corresponding load-shifting potentials is derived from the individuals' traveled distances, and several averaging assumptions: energy consumption (0.2 kWh/km), charging power (3.7 kW), battery size (60 kWh), and minimum range (minimum range represents the minimum range requested by customers that will always be recharged instantaneously after plugging-in an EV for charging). (100 km [45]). Vehicle parameters are loosely based on the 2019 version of the Nissan Leaf (Energy consumption: 20.6–18.5 kWh/100 km, battery size: 40 or 62 kWh, cf. www.nissan.de/fahrzeuge/neuwagen/leaf/reichweite-aufladen.html), the most popular battery electric vehicle model worldwide [54]. Behind the low charging power lies the assumption that most vehicle owners charge at home or at work [26] where no dedicated charging points are available due to costs and ample time spent plugged-in. With these simple assumptions, we intend to make the results as transparent as possible. In addition to that, the corresponding effects of varying these parameters are evaluated by conducting sensitivity analyses in Section 5.2.

Of the 6 mn individuals adopting PEV in France and in Germany, 5.5 mn of the German adopters (represented by 4487 data records) and 5.9 of the French adopters (represented by 4942 data records) charge their PEV at home or at the workplace on the reference day. The 5.5 mn German adopters charging at home or at the workplace charge their PEV in 10.4 mn charging processes and the 5.9 mn French PEV adopters during 12.2 mn charging processes. Hence, in the scenario considered (PEV can be charged at home and at the workplace), PEV users charge twice per day on average. Plug-in times, active charging times, load-shifting potentials, and the energy charged only differ slightly between France and Germany (cf. Table 3). If vehicles are not parked at home or at work, they are not charged.

Table 3. Charging behavior with two methods over different scenarios.

	France		Germany	
	Original Sample	Reduced Sample	Original Sample	Reduced Sample
PEV adopters charging in sample	4942	967	4487	930
Represented number of PEV adopters charging	5.9 mn	6.0 mn	5.5 mn	5.1 mn
Charging events of sampled PEV adopters	8873	1700	8590	1756
Represented charging events	11.8 mn	12.2 mn	10.4 mn	9.5 mn
Plug-in time Δt_x^{plug}	Mean	10.36 h	9.94 h	9.93 h
	Std. Dev.	7.23 h	7.76 h	7.75 h
	Median	9.67 h	11.64 h	11.42 h
Active charging time Δt_x^{active}	Mean	1.56 h	1.35 h	1.39 h
	Std. Dev.	2.18 h	2.32 h	2.39 h
	Median	0.82 h	0.77 h	0.79 h
Load-shifting potential Δt_x^{LSP}	Mean	8.80 h	8.59 h	8.53 h
	Std. Dev.	7.12 h	7.59 h	7.58 h
	Median	7.81 h	9.09 h	8.66 h
Energy charged per charging event	Mean	5.77 kWh	4.99 kWh	5.15 kWh
	Std. Dev.	8.07 kWh	8.60 kWh	8.86 kWh
	Median	3.04 kWh	2.84 kWh	2.92 kWh
Total energy charged per day E^{total}	60.82 GWh	60.82 GWh	59.96 GWh	59.96 GWh
Total energy directly charged per day E^{direct}	1.65 GWh	2.26 GWh	2.06 GWh	2.92 GWh
Total energy flexibly charged per day E^{flex}	59.16 GWh	58.56 GWh	57.90 GWh	57.04 GWh

Total energy charged per day represents the energy charged for the pure electric mileage of the PEV adopters simulated. That is, an increase in the charging power or the range-specific parameter potentially results in an increase in the total energy charged per day. Our sensitivity analyses in Section 5.2. show the effects of varying input parameters on total energy charged and total energy flexibly charged.

Figure 3 visualizes the cumulated French and German PEV load profiles: the load profile of direct PEV charging and the variations in the profiles of flexible, i.e., controlled charging. A flexible charging algorithm [45] is applied to hourly price profiles generated with an agent-based simulation model of the countries' power markets [15,55]. The distributions of the charging profiles in France and Germany look quite similar. In both countries, load peaks of 12 GW can be observed, and PEV-specific loads are shifted into nighttime and noon hours due to lower day-ahead market prices in these hours. Evening peaks when charging directly seem to be higher in France.

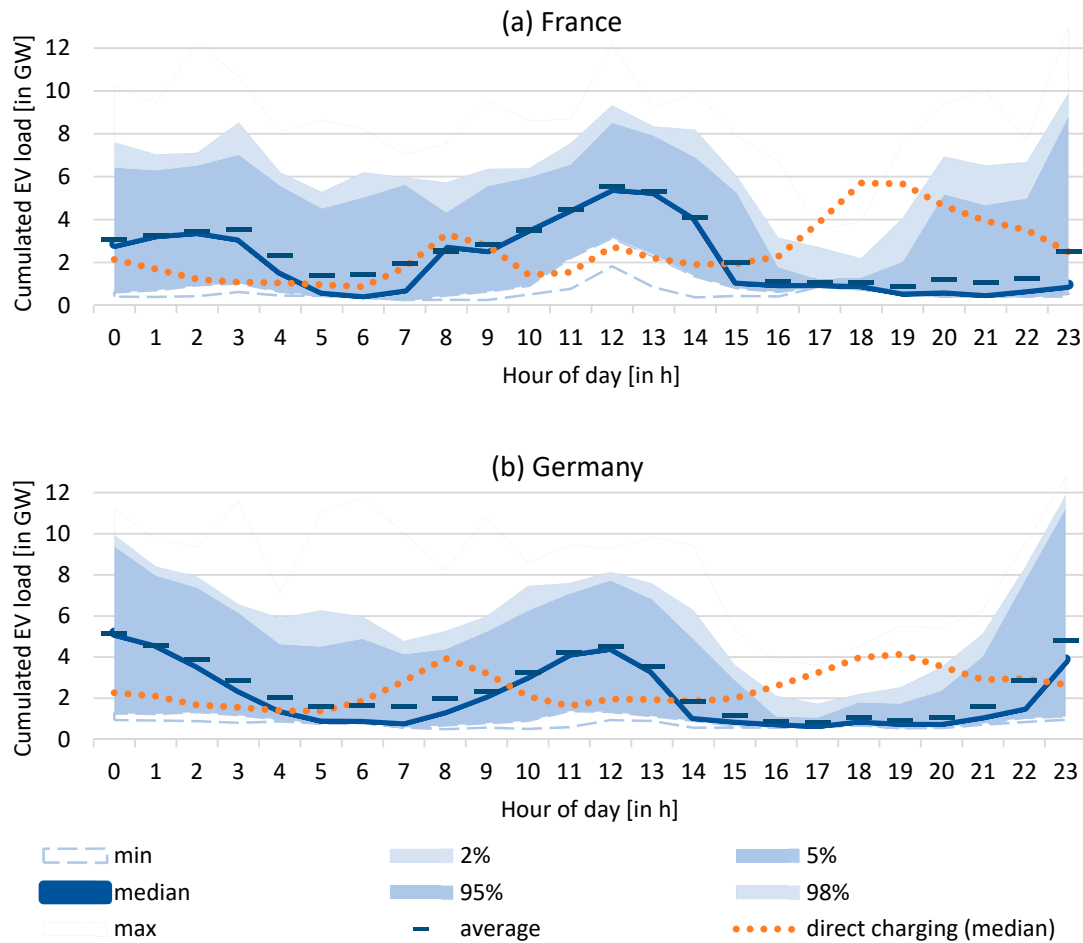


Figure 3. Cumulated daily PEV load of direct and controlled PEV charging in (a) France and (b) Germany in 2030.

4.3. Effects of Re-Sampling Approach

Detailed modeling of PEV diffusion, adoption, and charging with the presented hybrid model and scheduling approach is computationally demanding, especially when simulating exponential PEV market penetration beyond 2025. In previous work, high computing times have limited such analyses (cf. [45]). Method 2 as presented at the end of Section 3.1.3. aims to reduce simulation times while maintaining the quality of the results.

For the purposes of this study, we consider 1000 PEV adopters in the reduced sample (cf. Figure 2). 967 of the sampled French adopters (representing 6.0 mn PEV adopters) and 930 of the German sampled adopters (representing 5.1 mn PEV adopters) charge in this case. Slight deviations can be observed between the reduced and the original samples concerning all of the parameters considered, with the exception of the total energy charged (cf. Table 3). The most unfortunate deviation occurs in total weighted PEV adoptions, virtually adding or removing hundreds of thousands of PEV adopters from the population. Deviations originate in the re-sampling method (Method 2), where only every other PEV adopter is picked (reduced sample), each with their individual weight or representativeness. This results in observable differences concerning, for example, total energy directly charged per day. However, as we focus on adequately simulating the aggregated energy demand of the national PEV fleet, we accept these deviations. As computing time of our scheduling algorithm scales linearly with the exponentially growing number of adopter records, corresponding reductions of computing times outweigh the drawbacks of approximations for secondary variables. In our case, reducing the sample size results in savings in computing time of

about 85% for the simulated year 2030. For later years, calculation times remain constant—despite exponential growth of adoptions and the resulting number of sampled adopters reaching more than 20,000 with Method 1.

While the yearly energy demand of PEV is kept equivalent for the reduced case (cf. Method 2), the daily profile of PEV charging is very important to their influence on the energy system. Figure 4 visualizes the deviations of the hourly cumulated charging demand in 2030 for the two markets in the direct charging scenario. Deviations between the reduced and the original samples are visually observable, but average out over the day.

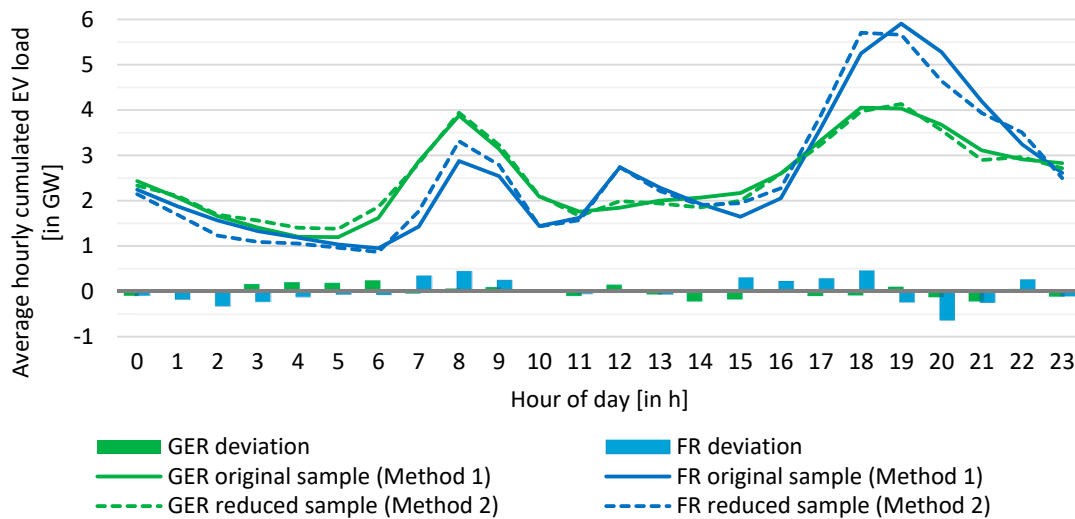


Figure 4. Average hourly cumulated PEV load of original and reduced sample directly charging in 2030.

5. Discussion

This discussion section aims to put the results in perspective. Section 5.1 discusses the hybrid diffusion model. Section 5.2. discusses sensitivities to PEV charging behavior in response to different parameter choices. Section 5.3. discusses limitations to our approach.

5.1. Hybrid Diffusion and Adoption Model for PEV

We use a hybrid PEV diffusion model in this study, i.e., we combine a bottom-up and a top-down approach [16] in order to better capture adopters' personal preferences as well as shifting macro-economic framework conditions [17]. As suggested by [16], the model presented in this study takes into account economic and social information (based on the bottom-up binary logistic modeling approach) as well as market development information (based on the top-down Bass diffusion model). By applying the binary logistic model, our modeling approach identifies early PEV adopters within representative mobility data sets, and their corresponding PEV charging behavior is simulated for France and Germany [41]. The approach can be directly applied to other markets, given sufficient availability of mobility studies and information on PEV diffusion targets. This is of significant use for modeling the impact of PEV on complex energy systems, as these systems are usually highly interconnected and even co-dependent, both physically and economically.

The results of our analyses show that PEV diffusion is significantly more dynamic in France than in Germany, a finding in line with other studies [52]. Since the Bass diffusion model is anchored in historical data and the same political target, the higher dynamics in France are likely the result of a stronger incentive situation for low-emitting vehicles in the French tax regime and lower power prices [56].

5.2. Sensitivity Analysis for PEV Charging

The results shown in Section 4.2 are based on the assumptions presented at the beginning of that section and define a base case (3.7 kW charging power, 60 kWh battery capacity, 100 km minimum range). In the following, we conduct sensitivity analyses in order to analyze the effects of parameter variation on total energy charged and total energy flexibly charged. The results presented in Figure 5 show that electric mileage increases with increasing battery capacities. However, it seems that with battery capacities of 60 kWh, a certain saturation level concerning full electric mileage when charging with 3.7 kW is reached (Figure 5a). Increasing the charging power further results in a growing share of full electric mileage (Figure 5b). In our simulations, sensitivities concerning the effects of charging power on electric mileage seem to be slightly higher in Germany than in France. Moreover, battery capacity variation affects the total energy flexibly charged during a day. A certain saturation level is reached when battery capacities approach 80 kWh (133%). As with total energy charged, total energy flexibly charged can be increased by increasing charging power (Figure 5b). Higher minimum range thresholds result in reduced total energy flexibly charged, although seemingly to a lesser degree than variations in battery capacity (Figure 5a).

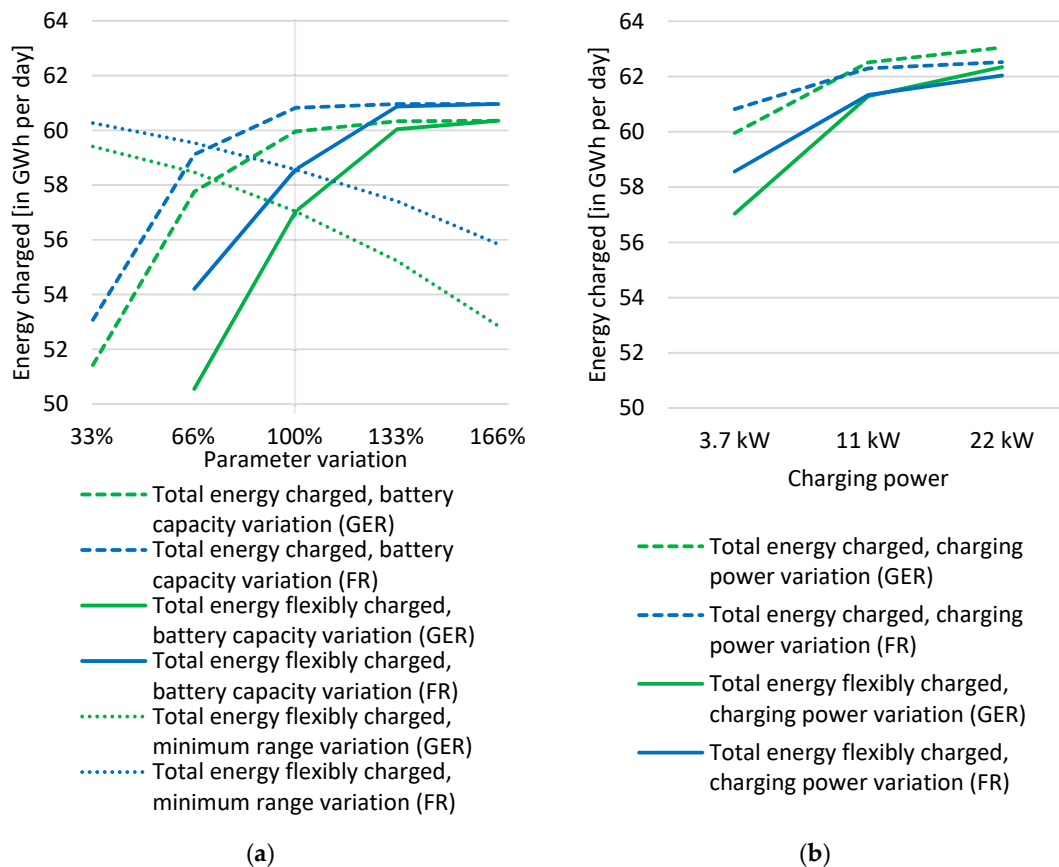


Figure 1: Sensitivity analysis concerning total energy charged and total energy flexibly charged, depending on (a) varying battery capacity, minimum range, and (b) charging power. Base case: charging with (a) 60 kWh battery capacity, 100 km minimum range, and (b) 3.7 kW.

5.3. Limitations

Naturally, our model suffers from several limitations: The Bass diffusion model neither considers nor anticipates policy changes, which can have significant effects on adoption of PEV. However, one could argue that governments might adjust their policies to incentivize a successful diffusion towards publicized goals. Looking at our calculation of charging potentials, our approach

focuses on the national charging potential. While this is sufficient for policy recommendations and trend analyses, implementation is another matter. A singular aggregator might dominate the market for flexible loads. Moreover, we assume participation of all PEV in the scheme, which is of course rather optimistic. A differentiation between customer groups and respective segmentation of fundamental parameters (for example, vehicle model selection) is a field of future research as, for example, the available electric range is likely to influence driving and recharging behavior [57–59].

Fundamentally, it is still uncertain in how far conventional driving behavior can be superimposed on PEV, as implied by using national mobility studies. On the other hand, we model adoption based on data from a stated preference survey from persons who have been using first-generation PEV mostly as company pool vehicles between 2011 and 2013 [39,41]. Mixing these two data sets implies methodological challenges and forces assumptions for the input data of several variables. However, using this model to attribute PEV adoption probabilities to individuals in representative mobility studies seems reasonable as an estimate to identify the sequence of PEV adoptions. The noticeable differences observed in the charging profiles when directly charging the vehicles indicate potentials for improvements concerning possibilities for charging activities at work, which could be addressed in future studies.

6. Conclusions and Outlook

For the estimation of potential systemic effects of PEV diffusion, for example, on the power grid, adequate PEV diffusion models are necessary, ideally with high topical and temporal granularity. The model presented in this study takes into account economic and social information (based on the bottom-up binary logistic modeling approach) as well as market development information (based on the top-down Bass diffusion model). By applying the binary logistic model to representative mobility studies, PEV adoption and a corresponding charging behavior are simulated for France and Germany. Results indicate that the reduced sample representing the PEV adopters in 2030 is decreased significantly, i.e., to 20% of the original sample while retaining all relevant information.

As these data sets include mobility behavior, and car use behavior in particular, we derive PEV adopter-specific use and charging behavior by assuming that all PEV adopters use their own PEV and that mobility behavior remains the same. This means that corresponding trips traveled with conventional cars are substituted by trips with PEV. In addition, we assume that PEV users have the possibility to plug in at work and at home and that PEV users do use this possibility. We compare the charging behavior derived from the PEV adopters' trip profiles and cumulated PEV-specific load profiles of France and Germany. On a disaggregated level, slight differences in the simulated charging behavior can be observed, for example, overall more charging events in France. Furthermore, on the aggregated level, small differences of cumulated PEV-specific load profiles are observable, for example, higher evening load peaks when directly charging PEV in France.

Our re-sampling approach (Method 2) limits the number of data records representing PEV adopters and corresponding charging events and results in drastically reduced computing times. This opens up new possibilities of including PEV on a disaggregated level in energy system modeling, for example, considering different PEV-specific charging strategies in investment decisions of power plant operators and considering PEV-specific effects throughout the whole simulation period in coupled wholesale electricity markets across Europe.

Sensitivity analyses show that PEV users' preferences concerning minimum ranges influence corresponding charging profiles. Total energy flexibly charged increases with decreasing minimum range thresholds. In addition, sensitivity analyses reveal the strong influence of preferences concerning battery size and charging power on the flexibility that PEV could provide for a more stable and affordable power system in times of increasing production uncertainty from renewable sources.

These results show that our model provides a useful tool for considering PEV in power-market and energy-system modeling. It could be used to analyze PEV-specific effects on power markets in order to inform policy makers on the potential effectiveness of different PEV diffusion and integration regulations—a popular lever on the way to a more sustainable transport sector.

Future work could focus on applying our advanced method of identifying PEV-specific load patterns to energy-system models in order to analyze potential future effects of PEV charging on electric-power systems. For improving specifically the adoption model, future analyses could focus on modeling PEV charging behavior more realistically, for example, based on observed charging and driving behavior of PEV.

Furthermore, increasing battery capacities of the vehicles coupled with increasing smart-charging experiences of PEV users might result in increasing acceptance of different smart-charging use-cases. The flexibilities identified in this analysis are charging event-specific, i.e., by the time of its next departure, the vehicle should be fully charged. Future work could analyze smart-charging activities based on higher flexibility potentials provided, for example, by considering the flexibility potentials available when shifting between charging events would be possible.

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