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Simulating Electric Vehicle Diffusion and Charging Activities in France and Germany

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Summary

Electric vehicles (EV) are considered to reduce oil dependency, noise and local air pollution as well as greenhouse gas emissions caused by road transportation. Today, an early market penetration phase already started and can be observed in many countries. But how could the diffusion and adoption of EV be modelled to create consistent scenarios? With which EV 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 modelling approach of an EV diffusion scenario consisting of a top-down macro-econometric Bass model answering the question at what point in time how many EV will be on the market, and a bottom-up micro-econometric binary logistic EV adoption model answering who is likely to adopt. This set of methods is applied on representative mobility data sets available for France and Germany in order to simulate driving and charging behaviors of potential French and German EV adopters. In addition, a sampling method is presented, which reduces computational times while intending to remain representative for the population of EV adopters considered. Results show that EV 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 EV differ slightly between France and Germany. Computational times can be reduced by our approach, resulting in the ability to better integrate EV diffusion, adoption and representative charging demand in bottom-up energy system models that simulate European wholesale electricity markets.

Keywords: Consumers, EV (electric vehicle), Germany, France, smart charging

1 Introduction

Greenhouse gas (GHG) emissions have a significant impact on the climate, leading to many associated undesirable side effects [1]. Moreover, fossil fuels are a finite resource. In Europe, realizing this 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 [2]. The share of the transport sector in European GHG emissions was 24 % in 2016 [3]. 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 effort necessary to achieve significant reductions [6]. In the global context, it is assumed that emissions in the transport sector could double due to rising energy demand in emerging countries [7]. This applies in particular to motorized private transport. Cars are responsible for around 12 % of 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]. Particularly in industrialized countries, the number of electric vehicle (EV) registrations has been rising continuously since 2008 [10] despite barriers specific to EV, such as limitations in range, a lack of charging infrastructure and high purchase prices [11].

For the estimation of potential structural effects of EV diffusion, e.g. on charging infrastructure and power supply, adequate EV diffusion models are necessary, showing at which point in time how many EV are being charged at which locations and how much energy they need to be charged. Therefore, this work answers the following research questions:

RQ1: How could the diffusion and adoption of EV be modelled for France and Germany?

RQ2: With which EV driving and charging behavior and load shifting potentials could this scenario be associated in France and Germany?

RQ3: What are the effects of a re-sampling approach intending to reduce computational effort?

Section 2 describes the methods and data used. Section 3 presents and discusses the results for the original and re-sampled case. Section 4 concludes and gives an outlook for future research.

2 Methods and data

To find adequate answers to the research questions, Section 2.1 describes the hybrid EV diffusion approach applied including a model variant intending to reduce computational effort. Section 2.2 describes the method deriving corresponding EV charging behavior of the EV adopters.

2.1 EV diffusion and adoption

Section 2.1.1 describes our application of the top-down macro-econometric Bass diffusion model. Section 2.1.2 a bottom-up micro-econometric binary logistic EV adoption model. Section 2.1.3 describes how these models interact and considers a model variant reducing computational effort.

2.1.1 Bass diffusion model

The Bass diffusion model is used to model EV diffusion in the market areas under consideration [12]. 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. For mathematical reasons, b is the parameter where $t - b = 0$. The number of cumulative adoptions up to time t, $N(t)$, is represented by equation 1:

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

Taking into account annual EV stock numbers, assumptions about medium-term governmental targets and the assumption 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 [13]), 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. EV are likely the first choice for meeting these fleet standards in the mid term, as suggested by growing investment in expansion of charging points and the upcoming portfolios of major vehicle manufacturers, even if alternative technology paths could be taken (e.g. fuel cell technology). A non-linear regression method is used to determine the parameters of the Bass EV diffusion scenarios for France and Germany (equation 1). Levenberg-Marquardt's numerical optimization algorithm [14, 15] is used for nonlinear curve fitting using OriginPro 2017G.

2.1.2 Binary logistic EV adoption model

In addition to knowing how many EV will be registered at a given time (Section 2.1.1), car companies and grid operators are interested to receive an answer to the question which customers will shift first to EV. Consequently, private purchase intentions for EV by German and French users of commercial EV were analyzed within the accompanying research activities of the project CROME [16]. 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 EV in these days. The conducted online survey included a question on whether the German and French EV users of commercial and public enterprises could imagine buying an EV privately in the next 10 years [17, 18]. In addition, the respondents were asked for further information on their mobility behavior, the role of the respondents in their companies, their experiences with EV, household income, car usage frequency, nationality and the number of cars in households in order to examine whether the data on future EV purchase decisions can be explained by these variables. Dependencies between EV adoption intentions and these variables are observable and can be described with a binary logistic regression model [18].

2.1.3 Hybrid EV diffusion modelling approach

Representative mobility studies are available for France and Germany [19, 20]. We assume that individuals currently using cars will also be using cars in the future and will eventually become EV users at a certain point in time. EV adoption probabilities $p_i^{PEV\ adoption}$ are calculated (Section 2.1.2) and assigned to every car driving individual $i \in I$ within each of the representative mobility studies [19, 20] as described in [21]. 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 get a sorted list of car users $I^{sort} = \{i \in I : p_1^{PEV\ adoption} \geq p_2^{PEV\ adoption} \geq \dots \geq p_I^{PEV\ adoption}\}$. $A_{\tilde{t}}^{Adopter\ set} \subseteq I$ represents the set of EV adopting individuals in a country in a certain year $\tilde{t}$.

We use two different approaches to determine the set of EV 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 in [21, 22]:

Pseudocode of Method 1

for all $\tilde{t}$ ***do***
    while $i \in I^{sort} \wedge W \leq N(\tilde{t})$
        Set $W = W + w_i$
        Add i to $A_{\tilde{t}}^{Adopter\ set}$
    end while
end for

According to the approach described with the pseudocode of Method 1 all car users $i \in I^{sort}$ become EV adopters $i \in A_{\tilde{t}}^{Adopter\ set}$ if their EV 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 EV adopters for that year.

As computing times of our heuristic EV charging algorithm [22] scale linearly with the number of adopters and corresponding charging events, which in turn grow exponentially with the growth of initial purchases [12], we use the alternative approach described in the pseudocode of Method 2. It limits the number of adopters to k^{limit} as well as their charging events, but still intends to be representative of the original EV adopting population considered $A_{\tilde{t}}^{Adopter\ set}$ identified with Method 1.

Pseudocode of Method 2

for all $\tilde{t}$ ***do***
    Set $\hat{I}_{\tilde{t}}^{sort} = \{I^{sort} \mid i\ mod\ z_{\tilde{t}} = 0\}$ with $z_{\tilde{t}} = nint\left(\frac{W^{A_{\tilde{t}}^{Adopter\ set}}}{k^{limit}}\right)$
    while $\hat{\imath} \in \hat{I}_{\tilde{t}}^{sort} \wedge \hat{\imath} \leq k^{limit}$
        Set $\hat{Q}^{\hat{A}_{\tilde{t}}^{Adopter\ set}} = \hat{Q}^{\hat{A}_{\tilde{t}}^{Adopter\ set}} + q_{\hat{\imath}}$
        Add $\hat{\imath}$ to $\hat{A}_{\tilde{t}}^{Adopter\ set}$
    end while
    while $\hat{\imath} \in \hat{A}_{\tilde{t}}^{Adopter\ set}$
        Set $\hat{w}_{\hat{\imath}} = w_{\hat{\imath}} \cdot \eta_{\tilde{t}}^{scaling}$ with $\eta_{\tilde{t}}^{scaling} = \frac{Q^{A_{\tilde{t}}^{Adopter\ set}}}{\hat{Q}^{\hat{A}_{\tilde{t}}^{Adopter\ set}}}$
    end while
end for

Method 2 first calculates $z_{\tilde{t}}$ in order to define a reduced sorted list of EV 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 EV adopter from I^{sort} of size k^{limit} (line 5). The adopter specific daily charging energy demand $q_{\hat{\imath}}$ 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 $Q^{A_{\tilde{t}}^{Adopter\ set}}$, producing the scaling factor $\eta_{\tilde{t}}^{scaling}$ for that year $\tilde{t}$. The scaling factor is applied to the original weight $w_{\hat{\imath}}$ for each adopter 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.

2.2 EV charging

The persons adopting EV in the representative French and German mobility studies are assigned reference date specific mobility profiles. We assume that the mobility patterns of car usage remain constant as long as the range of the EV is sufficient for the trip lengths. If the pure electric range is not sufficient, we assume that the EV are equipped with combustion engine driven range extenders. We assume the same car usage behavior on every day of the simulation and a 1:1 relation between EV adopters and EV. As vehicles park most of the time at home or at the workplace [20], load shifting potentials are highest at these locations. Therefore, we assume that EV adopters have the possibility to charge their cars at home and at work. Combining driving and parking profiles with assumptions on EV energy consumption, battery capacity and available charging power, allows to determine the energy requirement and the load shifting potential of each charging process [21–23].

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

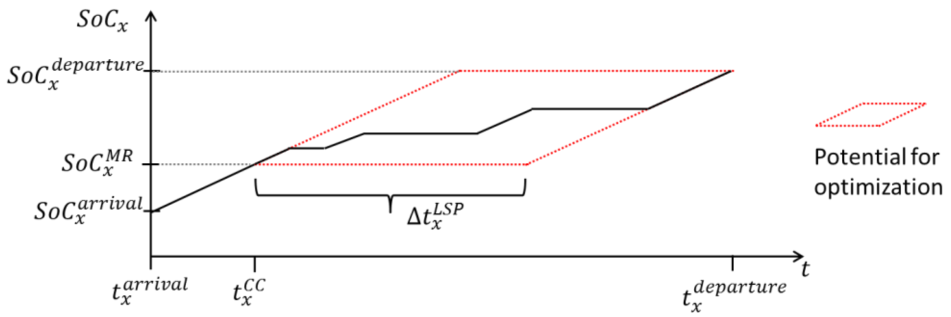

Figure 1: EV charging event x with load shifting potentials

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

$$\Delta t_x^{plug} = t_x^{departure} - t_x^{arrival} \tag{2}$$

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

$$\Delta t_x^{active} = \frac{SoC_x^{departure} - SoC_x^{arrival}}{P_x^{max}} \tag{3}$$

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

$$\Delta t_x^{LSP} = \Delta t_x^{plug} - \Delta t_x^{active} \tag{4}$$

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

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

Total energy directly charged E^{direct} is calculated by adding the energy directly charged of the single charging events (equation 6).

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

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

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

3 Results and discussion

Section 3.1 describes the EV diffusion scenarios developed for the French and German market intending to provide an answer to RQ1. Section 3.2 presents the simulation results of EV charging and compares the effects of the re-sampling method applied (Method 2) on the results in order to provide an answer to RQ2 and RQ3.

3.1 EV diffusion and adoption

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

Table 1: Data used for diffusion model estimation

EV stock	France		Germany	
End 2009	-	[24]	3032	[25]
End 2010	3368		4404	
End 2011	6167		8670	
End 2012	12,805		13,582	
End 2013	22,217		23,208	
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 [26]		6,000,000 [27]	
Total vehicle stock (M)[1]	32,675,972 [24]		45,803,560 [25]	

The French public authorities' expectations of six million EV in 2030 [26] are in line with the government targets set in Germany [27]. These expectations are taken into account in the scenario calculations resulting in the Bass diffusion model parameters shown in Table 2.

These two EV diffusion scenarios are rather optimistic scenarios. The innovation coefficient (p) of the French EV diffusion scenario is considerably higher compared to the German's (cf. Table 2). However, imitation coefficients (q) are on a similar level. According to Figure 2 the models' forecasts of EV stock are well below the original national policy targets in France (2 mn in 2020 and 4.5 mn in 2025, [28]) and Germany (1 mn [27]).

Based on historical new registrations for 39 countries, innovation and imitation coefficients of Bass diffusion models have been estimated by [29] (France: $p = 1 \cdot 10^{-4}$ and $q = 0.4$; Germany: $p = 2.5 \cdot 10^{-5}$ and $q = 0.5$). The innovation coefficients for Germany and France in our results are somewhat higher (France: $p = 1.44 \cdot 10^{-4}$; Germany $p = 4.31 \cdot 10^{-5}$), but relatively low in comparison to other common innovation coefficients averaging $p = 0.03$ [29, 30]. The estimated imitation coefficients are slightly below the average of $q = 0.38$ [29, 30]

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

(France: q = 0.31; Germany: q = 0.32), but are comparable with other innovations [30]. Differences could be due to the fact that only sales figures of zero emission EV were included in [29], but all types of plug-in EV are considered in our study.

Table 2: Bass diffusion model parameters

Parameter	France		Germany	
	M	SD	M	SD
p	$4.31 \cdot 10^{-5}$	$2.67 \cdot 10^{-5}$	$1.44 \cdot 10^{-4}$	$1.82 \cdot 10^{-5}$
q	0.32	0.004	0.31	0.0015
b	2008.22	5.82	2010.01	1.05
M	32,675,972		45,803,560	
R^2	~ 1		~ 1	

To answer the question of who adopts EV in France and Germany, we identify persons adopting EV in representative mobility data sets [19, 20]. 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 travelled and corresponding vehicles used.

EV adoption probabilities are assigned to the persons interviewed in the national mobility studies using the binary logistic EV adoption model as described in Section 2.1. The higher the probability of EV adoption, the earlier these persons are assumed to adopt EV.

The two different methods (Methods 1 and 2) are subsequently applied in order to obtain the original and the reduced EV adopter samples. Exemplary results are shown in Figure 2.

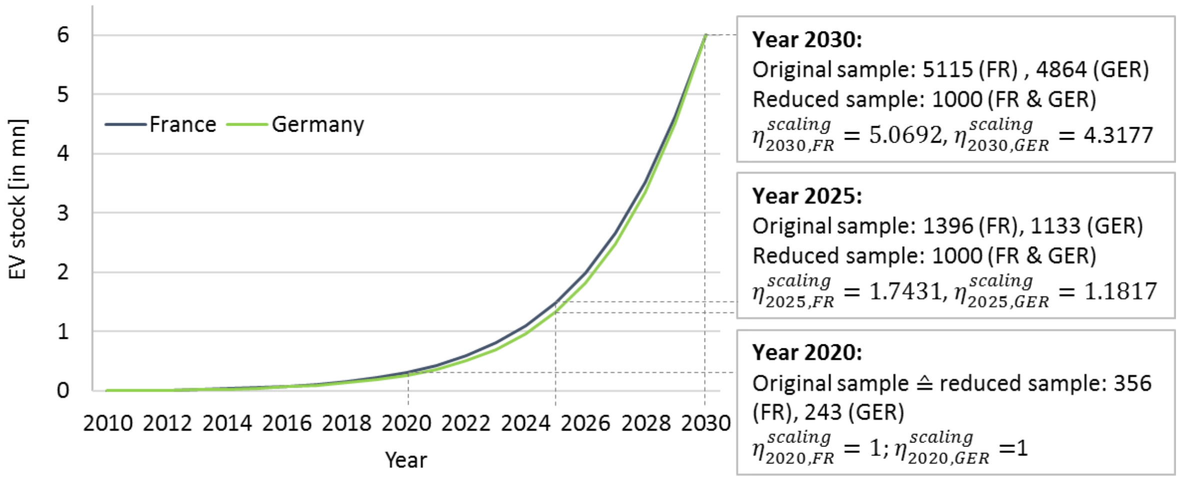

Figure 2: EV diffusion scenarios for France and Germany

3.2 EV charging

For the simulation of charging behavior, we assume that EV are charged at home and at work. Information on charging behavior and corresponding load shifting potentials is derived from the information on the distances travelled, consumption assumptions (0.2 kWh/km), assumed charging power (3.7 kW), battery size (60 kWh) and minimum range[2] (100 km). With these simple assumptions, we intend to make the results as transparent as possible. In addition to that, corresponding effects of varying these parameters are evaluated by conducting sensitivity analyses (Figure 5).

Of the 6 mn individuals adopting EV in France and 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 EV at home or at the workplace on the reference day. The 5.5 mn German adopters charging at home or at the workplace

[2] Minimum range represents the minimum range requested by customers that will always be recharged instantaneously after plugging-in an EV for charging.

charge their EV in 10.4 mn charging processes and the 5.9 mn French EV adopters during 12.2 mn charging processes. Hence, in the scenario considered (EV can be charged at home and at the workplace) on average EV users charge twice per day. Plug-in times, active charging times, load shifting potentials and the energy charged only differ slightly between France and Germany (cf. Table 3). In case vehicles are not parked at home or at work, they are not charged.

Table 3: Charging behavior in different scenarios considered

		France		Germany	
		Original sample	Reduced sample	Original sample	Reduced sample
EV adopters charging in sample		4942	967	4487	930
Represented number of EV adopters charging		5.9 mn	6.0 mn	5.5 mn	5.1 mn
Charging events of sampled EV 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}	M	10.36 h	9.94 h	9.93 h	10.59 h
	SD	7.23 h	7.76 h	7.75 h	7.24 h
	MED	9.67 h	11.64 h	11.42 h	9.58 h
Active charging time Δt_x^{active}	M	1.56 h	1.35 h	1.39 h	1.70 h
	SD	2.18 h	2.32 h	2.39 h	2.19 h
	MED	0.82 h	0.77 h	0.79 h	0.82 h
Load shifting potential Δt_x^{LSP}	M	8.80 h	8.59 h	8.53 h	8.88 h
	SD	7.12 h	7.59 h	7.58 h	7.16 h
	MED	7.81 h	9.09 h	8.66 h	7.89 h
Energy charged per charging event	M	5.77 kWh	4.99 kWh	5.15 kWh	6.31 kWh
	SD	8.07 kWh	8.60 kWh	8.86 kWh	8.12 kWh
	MED	3.04 kWh	2.84 kWh	2.92 kWh	3.04 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 EV adopters simulated. I.e. an increase of the charging power or the range specific parameter potentially results in an increase of the total energy charged per day. Our sensitivity analyses towards the end of this section show the effects of varying input parameters on total energy charged and total energy flexibly charged.

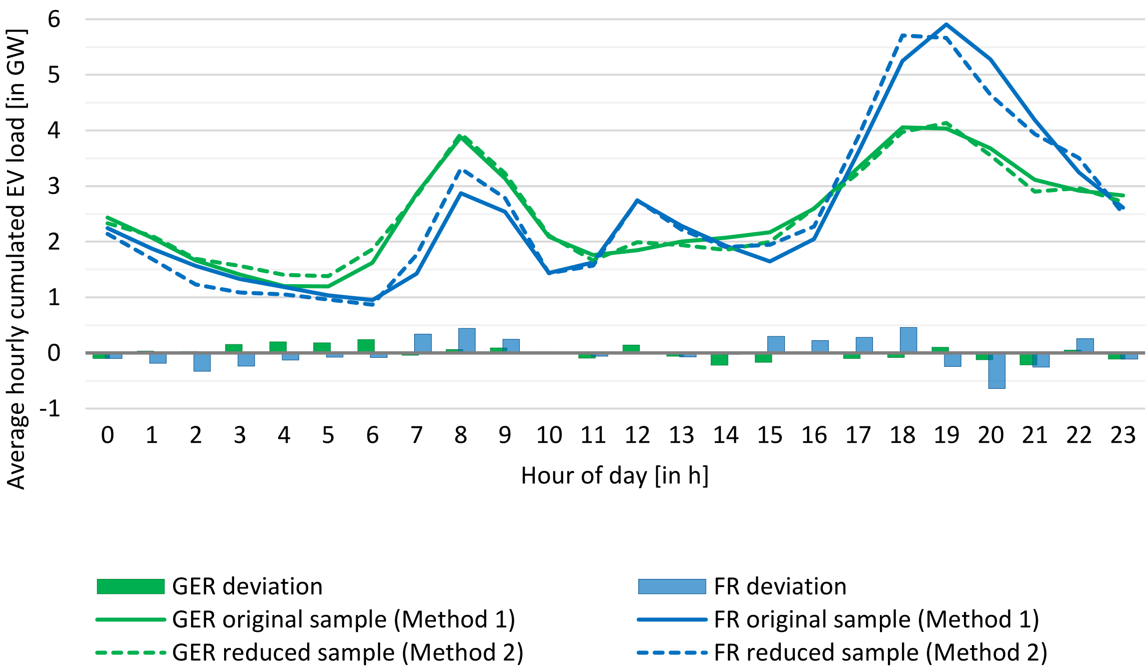

Figure 3: Average hourly cumulated EV load of original and reduced sample directly charging in 2030

1000 EV adopters are considered in the reduced sample. 967 of the sampled French adopters representing 6.0 mn EV adopters and 930 of the German adopters representing 5.1 mn EV adopters are charging 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 EV adoptions, virtually adding or removing hundreds of thousands of EV adopters from the population. Deviations originate in the re-sampling method (Method 2), where only every other EV adopter is picked (reduced sample). E.g. this results in differences observable concerning total energy directly charged per day. However, as we focus on adequately representing the aggregated energy demand of the national EV 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 these approximations. Reducing the sample size results in savings in computing time of about 85 % in the year 2030.

Figure 3 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 visualizes the cumulated French and German EV load profiles. The load profile of direct EV charging and the variations in the profiles of flexible, i.e. controlled charging. 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 EV specific loads are shifted into nighttime and noon hours due to lower day-ahead market prices in these hours. Evening peaks when directly charging seem to be higher in France.

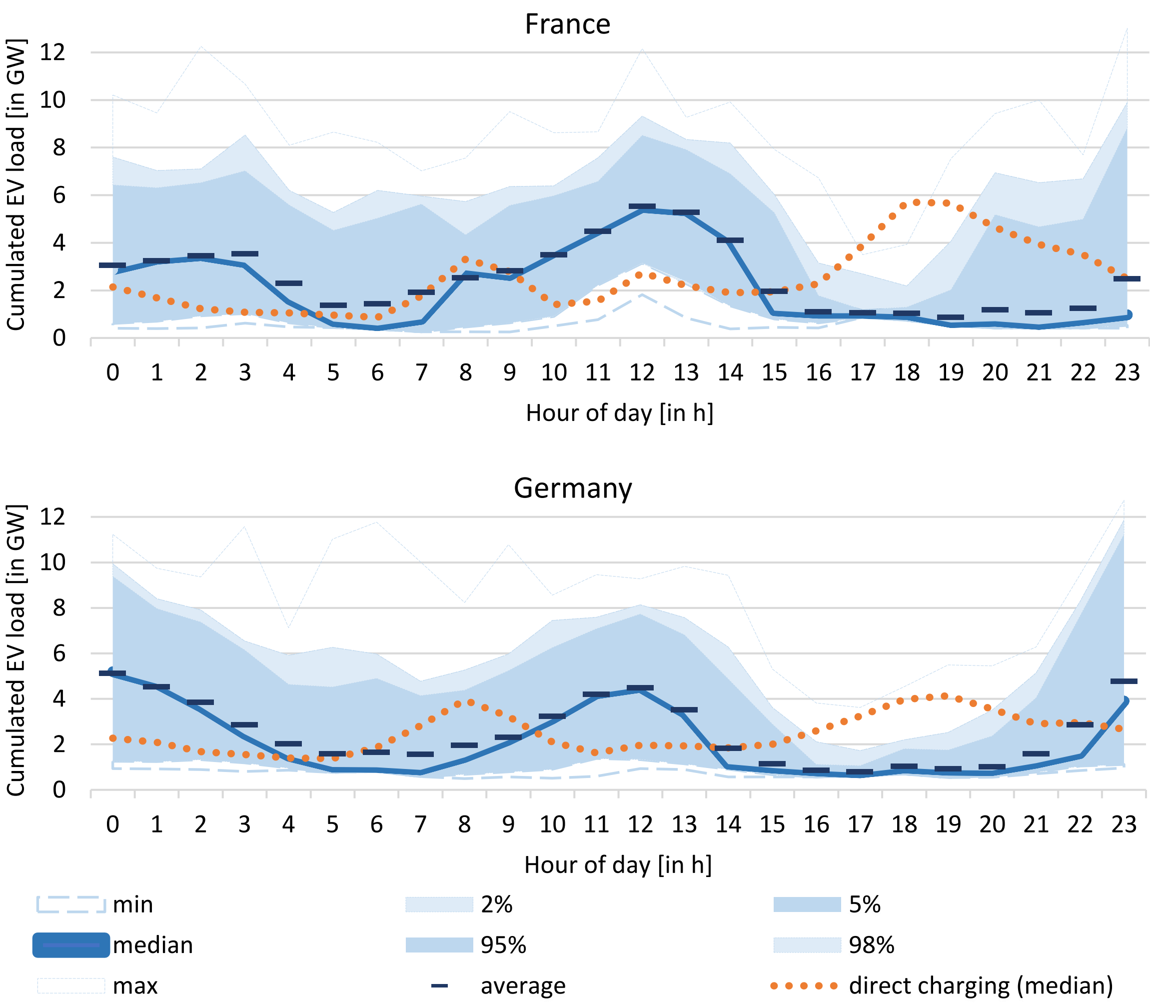

Figure 4: Cumulated EV load of direct and controlled charging in France and Germany in 2030

These results are based on the assumptions presented in Section 3.2 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 5, left hand side). Further increasing charging power results in further increasing the share of full electric mileage (Figure 5, right hand side). In our simulations, sensitivities concerning effects of charging power on electric mileage seem to be slightly higher in Germany. Furthermore, battery capacity variation affects the total energy flexibly charged during a day. A certain saturation level is reached when battery capacities reach 80 kWh (133 %). As with total energy charged, total energy flexibly charged can be increased by increasing charging power (Figure 5, left hand side). Increasing minimum range thresholds result in a reduction of total energy flexibly charged, although seemingly to a lesser degree than variations to battery capacity.

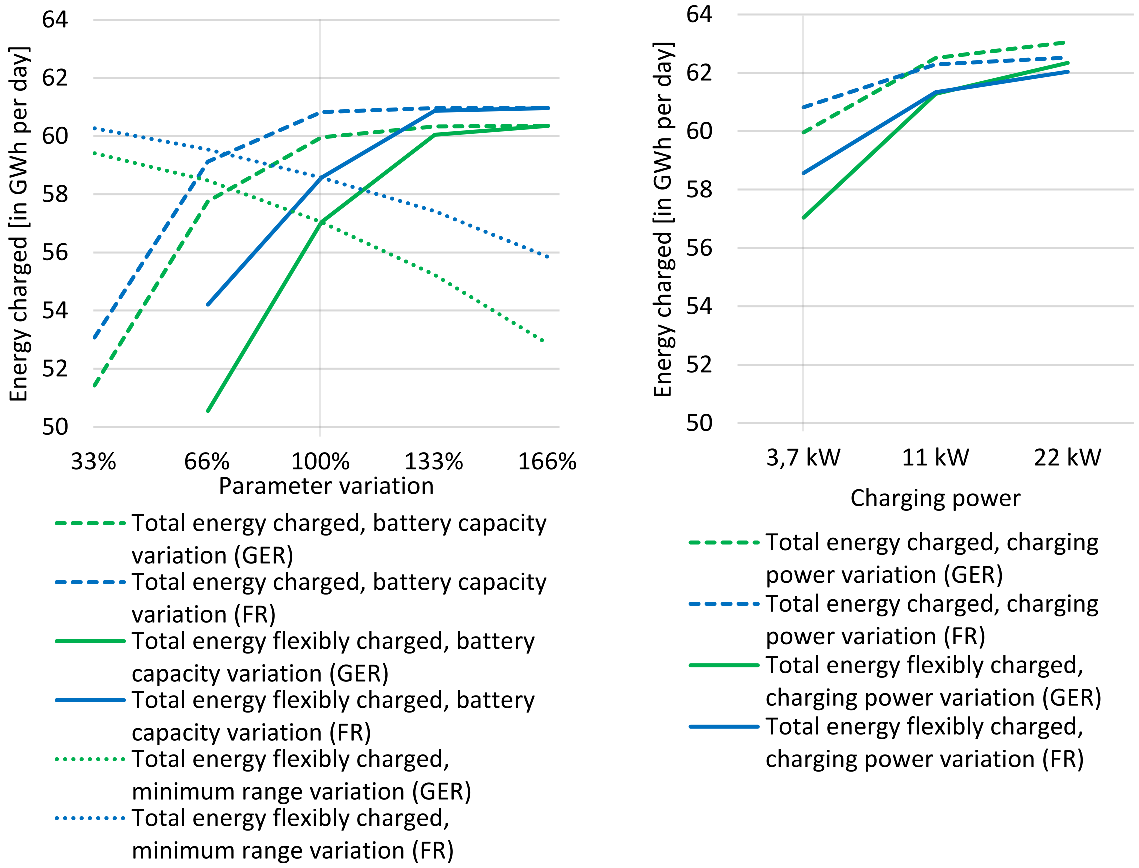

Figure 5: Sensitivity analysis concerning total energy charged and total energy flexibly charged, depending on varying battery capacity, minimum range and charging power. Base case: Charging with 3.7 kW, 60 kWh battery capacity and 100 km minimum range

4 Conclusion and outlook

We use a hybrid EV diffusion model in this study, i.e. we combine a bottom-up and a top-down approach [31]. Such modelling approaches are recommended by various studies on market developments of car ownership [31–34]. 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 EV penetration models [35]. First studies address this [36]. Disaggregated survey data enable forecasts of potential future market developments already in early market phases [31] and enable the analysis of effects of varying input parameters on market developments [36]. EV penetration models based on aggregated data, on the other hand, are suitable for medium- to long-term forecasts, as long as a sufficient amount of market development data is available [31].

As suggested by [31], the model presented in this study takes into account economic and social (based on the bottom-up binary logistic modelling 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, EV adoption and corresponding EV charging behavior is simulated for France and Germany.

The results of our analyses show that EV diffusion is more dynamic in France than in Germany. This finding is in line with other studies [29]. With respect to EV adoption, our modelling approach identifies early EV adopters within mobility data sets representative for France and Germany by applying a binary logistic regression model based on stated preferences of EV users [18].

As these data sets include mobility behavior, car usage behavior in particular, we derive EV adopter specific usage and charging behavior by assuming that all EV adopters use their own EV and that mobility behavior remains the same, i.e. corresponding trips travelled with conventional cars are substituted by trips with EV. In addition to that, we assume that EV users have the possibility to plug-in at work and at home and that EV users indeed use this possibility. We compare the charging behavior derived from the EV adopters' trip profiles and cumulated EV specific load profiles of France and Germany. Slight differences in the simulated charging behavior on a disaggregated level can be observed (e.g. overall more charging events in France). Furthermore, slight differences on the aggregated level of cumulated EV specific load profiles are observable (e.g. higher evening load peaks when directly charging EV in France). Future analyses could focus on modelling EV charging behavior more realistically, e.g. based on observed behavior concerning plugging-in EV.

Our re-sampling approach (Method 2) limiting the number of data records representing EV adopters and corresponding charging events results in high gains concerning computing times. This results in new possibilities of considering EV on a disaggregated level in energy system modelling, e.g. considering different EV specific charging strategies in investment decisions of power plant operators and considering EV specific effects throughout the whole simulation period in coupled wholesale electricity markets across Europe. In prior work high computing times limited such analyses [21]. Future work could focus on applying this advanced method of identifying EV specific load patterns to energy system models in order to analyze potential future effects of EV charging on electric power systems.

Acknowledgements

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