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Modeling and evaluating bidirectionally chargeable electric vehicles in the future European energy system

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Abstract

In addition to a massive expansion of renewable energies, a successful change towards a decarbonized energy system requires the flexibilization of consumers and the integration of storage and sector coupling technologies. Bidirectionally chargeable electric vehicles (EVs) represent such a consumer flexibility. They are able to charge when there is an electricity generation surplus and to discharge when there is a shortage in electricity generation. Therefore, they can act as a storage from the perspective of the energy system. This paper analyzes different modeling approaches of bidirectionally chargeable EVs in large-scale energy systems and evaluates the impact of bidirectionally chargeable EVs on the future European energy system design. We compare the modeling of discrete EV profiles, clustered EV profiles as well as an aggregated EV profile with simplified constraints. Aggregation of EV profiles per country leads to significantly lower computation times, while still achieving results close to the reference case. The number of bidirectionally chargeable EVs in a cost optimal future European energy system increases from 6 million EVs in 2025 to over 60 million EVs in 2050. We show that bidirectionally chargeable EVs lead to a better integration of PV generation, to lower installed capacities of gas- and hydrogen-fired power plants as well as stationary battery storages. They also lead to decreasing electricity prices and total European energy system costs.

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1. Introduction

In order to achieve the European climate protection targets, the future European energy system will be strongly characterized by volatile renewable energies [1]. Numerous studies analyze a future decarbonized energy system at the national level [2]. Due to the increase in renewable energies, additional flexibility is necessary to balance

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electricity generation and consumption in the energy system. Electric vehicles (EVs) represent a possible large demand-side flexibility. Smart charging allows EVs to charge when there is a surplus of electricity generation. Bidirectional charging allows to charge smartly, and even feed electricity back into the system when there is a shortage of electricity generation [3]. There are multiple use cases for bidirectionally chargeable EVs [4]. In vehicle-to-home (V2H) applications, energy from the EV is fed back into the household (on the energy user's side of the meter). Vehicle-to-grid (V2G) applications feed-back energy into the grid. The added value of bidirectionally chargeable EVs for the future energy system has not yet been sufficiently investigated. Therefore, in this paper we investigate modeling approaches of bidirectionally chargeable EVs in energy system models and resulting system-optimal penetration rates of smart and bidirectionally chargeable EVs in the future European energy system.

Numerous papers discuss the modeling of bidirectionally chargeable EVs from the user's perspective [5]. In V2H applications they must be modeled with varying charging and discharging efficiencies, since low power flows in a household lead to low efficiencies that cannot be modeled by one fixed efficiency [6]. Kern et al. show that revenue potentials vary strongly depending on user behavior, electricity prices and feed-in tariffs as well as other household components and usually range from 200 to 500 €/EV/a. Salpakari et al. model V2H applications in a household with a photovoltaic (PV) system in Sweden, quantify the annual electricity cost savings to 8% to 33% and show the impact on battery degradation [7]. Charging and discharging powers in V2G applications, like arbitrage trading, are usually at maximum charging and discharging power. Therefore, modeling a fixed charging and discharging efficiency is sufficient here [8]. Bidirectionally chargeable EVs can significantly reduce charging costs and even generate revenues to the owner of the EV [9]. Revenue potentials vary strongly depending on the EV and electric vehicle supply equipment (EVSE) characteristics, the regulatory framework, user behavior, and electricity market prices and usually range from 100 to 1000 €/EV/a [8]. Since all aforementioned studies focus on the modeling of individual bidirectionally chargeable EVs, the impacts of bidirectionally chargeable EVs on the energy system are not evaluated. For example, neglected repercussions of EVs participating in the spot markets on electricity market prices potentially lead to overestimated revenues. Therefore, we model smart and bidirectionally chargeable EVs with a cost-optimal penetration rate in the energy system and estimate their revenues in future electricity markets.

There are some studies that discuss the impact of bidirectionally chargeable EVs on the electricity markets. Hanemann et al. discuss the flattening effect of EVs on electricity demand and electricity prices depending on the smart or bidirectional charging strategy of the EVs [10]. However, they model bidirectionally chargeable EVs highly simplified regarding the EV profiles and EV constraints and limit the observation area to Germany. Rodríguez et al. also show the smoothing effect of bidirectionally chargeable EVs on the electricity demand of Bogotá D.C. in Colombia, South America, resulting in a higher load factor [11]. However, once again the observation area is small and the modeling of the EVs is highly simplified. Huang et al. model the large-scale penetration of electric vehicles by a simplified charging behavior that is only according to statistic customers' travel needs [12]. They show that bidirectionally chargeable EVs can ensure the safe operation of distribution systems, but do not discuss repercussions on the energy system. Wei et al. optimize energy system planning with V2G applications and show the positive economic and environmental effect of V2G on the energy system [13]. However, the modeled EV fleet is simplified by stochastic features and the observation area is limited to cities, which leads to different requirements for the modeling approach compared to large energy systems. Child et al. show the decreasing impact of bidirectionally chargeable EVs on the need for storage and generation capacity for the Åland Islands near Finland [14]. In this paper, we also evaluate the impact of bidirectionally chargeable EVs on energy system components, such as electric storages and generation capacities. However, we will focus on the modeling approaches of bidirectionally chargeable EVs in more detail. Additionally, we evaluate their impact on total energy system costs and electricity prices in the European energy system.

None of the aforementioned studies model cost-optimal penetration rates of bidirectionally chargeable EVs in a highly coupled, large-scale multi-energy carrier system, since the optimization problem quickly becomes very complex. In this paper, we address this research gap. We formulate and analyze different modeling approaches of bidirectionally chargeable EVs and publish resulting EV profiles. In our results section, we use the best fitting modeling approach to evaluate cost-optimal penetration rates of bidirectionally and smart chargeable EVs in the future European energy system from 2025 to 2050. Therefore, this paper provides policy recommendations for action, i.e., where and when to promote the new technology of bidirectionally chargeable EVs in Europe. Furthermore, stakeholders in the field of energy can align business models with the cost-optimal expansion of this new technology. Ultimately however, scientists can also use the modeling approaches and the EV profiles for their own energy system analyses.

2. Methodology

2.1. Modeling approaches of V2G applications in energy system models

Bidirectionally chargeable EVs are modeled like stationary storage systems with additional constraints on availability and driving consumption. Therefore, the absolute battery state of charge (SoC) $SoC\,(t)$ in a timestep t is determined by the absolute battery SoC of the previous timestep $SoC\,(t-1)$ added to the charged energy $P_c\,(t)\cdot\eta_c\cdot\Delta t$ and subtracted by the discharged energy $\frac{P_d(t)}{\eta_d}\cdot\Delta t$ and the driving consumption $P_{con}\,(t)\cdot\Delta t$, where Δt is the time step length. P_c and P_d refer to charging and discharging powers, while η_c and η_d describe charging and discharging efficiencies.

$$SoC\,(t) = SoC\,(t-1) + P_c\,(t)\cdot\eta_c\cdot\Delta t - \frac{P_d\,(t)}{\eta_d}\cdot\Delta t - P_{con}\,(t)\cdot\Delta t \tag{1}$$

To model realistic user behavior, we introduce Eqs. (2) and (3) that further constrain the SoC. The minimum percentage safety SoC min_{safe} in Eq. (2) represents the requirement to perform a safety-related drive, like a drive to the hospital, at any time when the EV is connected. The minimum percentage SoC at departure min_{dep} respects the user's desire of a minimum SoC of the EV battery when departing. The relative parameters min_{safe} and min_{dep} are multiplied by the maximum absolute SoC SoC_{max} to compare it to the absolute state of charge $SoC\,(t)$. If the EV is not connected to an EVSE, min_{safe} and min_{dep} are set to zero, since there is no minimum SoC desired by the user.

$$SoC\,(t) \geq SoC_{max}\cdot min_{safe} \qquad \text{for all timesteps } t \text{ with connected EV} \tag{2}$$

$$SoC\,(t) \geq SoC_{max}\cdot min_{dep} \qquad \text{for all timesteps } t \text{ with departing EV} \tag{3}$$

Furthermore, usual constraints restrict the charging and discharging power by maximum values $P_{c,max}$ and $P_{d,max}$ as well as the battery SoC by a parameterized maximum SoC_{max} in Eqs. (4)–(6) for all considered timesteps t. If the EV is not connected, $P_{c,max}$ and $P_{d,max}$ are set to zero, since charging and discharging is not possible.

$$P_c\,(t) \leq P_{c,max} \qquad \text{for all timesteps } t \text{ with connected EV} \tag{4}$$

$$P_d\,(t) \leq P_{d,max} \qquad \text{for all timesteps } t \text{ with connected EV} \tag{5}$$

$$SoC\,(t) \leq SoC_{max} \qquad \text{for all timesteps } t \tag{6}$$

Since the modeling of the European energy system is a highly complex optimization problem, the integration of every single EV as a discrete element in the energy system model would lead to unacceptable computing times. For this reason, we further discuss three modeling approaches of bidirectionally chargeable EVs in energy system models. The described modeling of bidirectionally chargeable EVs can be equally applied for smart chargeable EVs with the restriction that the discharging power of the EVs is set to zero.

Modeling of bidirectionally chargeable EVs with discrete EV profiles

In the first approach, we model EVs by discrete driving and location profiles. The EV consumption profile sets the variable $P_{con}\,(t)\cdot\Delta t$ in Eq. (1). The EV location profile is transferred to an EV connection profile. Depending on the modeled location of the EV supply equipment (at home, at work or in a public space), the EV status is connected or not connected. The connection status of the EV sets the variables in Eqs. (2)–(5).

Since the number of EVs in the future European energy system will increase to multiple millions, there is still a need to lower the number of discrete profiles. In an evaluation of synthetic EV profiles based on a mobility study in Germany in 2017 [15], Fattler shows that 10,000 discrete EV profiles are statistically viable to represent the average German mobility behavior [16]. Randomly drawing 1000 EV profiles from this pool of 10,000 EV profiles leads to a deviation of indicators, such as equivalent full cycles or daily charging hours of below 3%. Therefore, in this approach, we integrate the bidirectionally chargeable EVs in the energy system model by 1000 synthetic EV consumption and location profiles.

Since 1000 modeled EV elements differ from the number of bidirectionally chargeable EVs integrated into the energy system in reality, a scaling factor is introduced to set the constraining variables in Eqs. (1)–(6). In Eq. (7), we calculate the scaling factor $f_{num,EVs}$ by the number of bidirectionally chargeable EVs n_{EVs} divided by 1000, which represents the 1000 equally weighted EV elements.

$$f_{num,EVs} = \frac{n_{EVs}}{1000} \tag{7}$$

The scaling factor is used to set the constraining variables according to Eqs. (8)–(11). The parameters of a single EV $E_{con,1EV}(t)$, $P_{c,max,1EV}$, $P_{d,max,1EV}$ and $SoC_{max,1EV}$ are multiplied by the scaling factor. As a result, one EV element represents $f_{num,EVs}$ EVs with the same features. One million integrated bidirectionally chargeable EVs, for example, would consequently result in one discrete EV element representing 1000 EVs.

$$E_{con}(t) = E_{con,1EV}(t) \cdot f_{num,EVs} \tag{8}$$

$$P_{c,max} = P_{c,max,1EV} \cdot f_{num,EVs} \tag{9}$$

$$P_{d,max} = P_{d,max,1EV} \cdot f_{num,EVs} \tag{10}$$

$$SoC_{max} = SoC_{max,1EV} \cdot f_{num,EVs} \tag{11}$$

Modeling of bidirectionally chargeable EVs with clustered, discrete EV profiles

Since 1000 discrete bidirectionally chargeable EV elements integrated in an energy system model might still lead to high computing times, we further reduce the number of EV elements by using clustering algorithms. We use a k-means algorithm for the clustering of EV profiles based on an approach shown by Schmidt-Achert et al. [17] to best represent the mobility behavior of EVs.

We define representative driving and location profiles for each cluster by a three-step approach. First, features for the clustering algorithm are defined. Since the location, and thus the availability, of the EVs is most important for the value of smart or bidirectional charging [8], the availability at home and at work for 6-hour time frames per weekday results in 56 features for the clustering, e.g., Monday from 0am to 6am is one feature. Second, a k-means clustering algorithm is applied to find a predefined number of clusters to represent the population best. Third, the best representative of a cluster is chosen. Like Schmidt-Achert et al. we also define representatives by minimizing the sum of maximum and mean error compared to the reference, instead of using the traditional selection of the closest representative to the centroid. This approach leads to an economically viable choice of representatives, e.g., avoiding unrealistic low availabilities.

In this paper, we develop clustered EV profiles by using the described approach for 5, 10, 20 and 50 clusters. Fig. 1 shows a comparison of defined features for the reference case of 1000 EV profiles (a) and a representation of EV profiles by 5 clusters (b). The fundamental characteristic of the reference can be represented well by the 5-cluster approach. The lowest availability of EVs at home is just below 60%, the availability of EVs at work from Monday to Friday from 6am to 6pm is around 20% and the availability of EVs elsewhere (meaning at public spaces or driving) mostly varies from 10% to 20%. However, one can recognize concise differences. The availability of EVs at home during the weekend is much higher for the clustered profiles, leading to lower availabilities at work and elsewhere in this time frame. The same EV profile differences can be recognized during the weeknights.

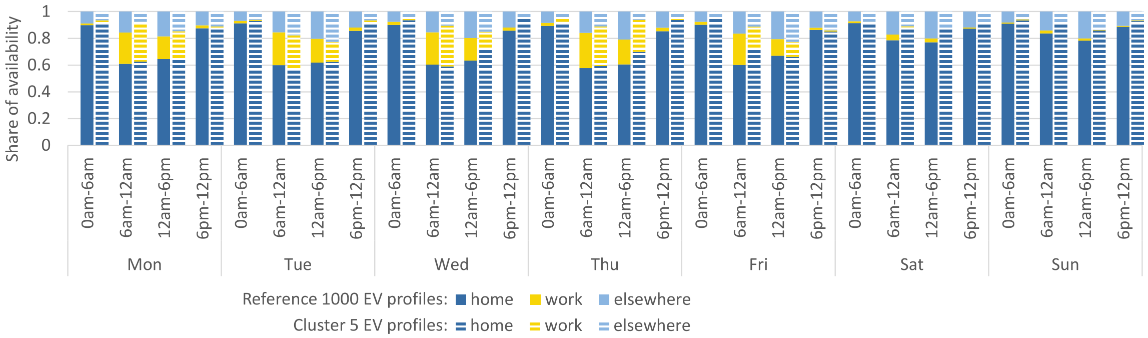

Fig. 1. Location of EVs in each feature for reference of 1000 EV profiles compared to 5 discrete clustered EV profiles.

In Table 1, we further analyze the different statistical behavior of clustered EV profiles (*CluX* for X discrete EV profiles) in comparison to the reference case of 1000 EV profiles (*Ref*). The overall mean availability of EVs at home, at work and elsewhere is represented quite well by the clustered profiles. However, one can observe that the deviation of all characteristics from the reference increases with a decreasing number of clusters. The availability of EVs at home is increasingly overestimated with a decreasing number of clusters and the availability of EVs

Table 1. Availability at home, at work or elsewhere for clusters *Clu50*, *Clu20*, *Clu10* and *Clu5* in comparison to reference scenario *Ref*.

	Mean availability					Max deviation from Ref				Mean deviation from Ref			
	Ref	Clu50	Clu20	Clu10	Clu5	Clu50	Clu20	Clu10	Clu5	Clu50	Clu20	Clu10	Clu5
Home	77.6%	79.5%	80.9%	81.0%	81.4%	6.5%	9.6%	10.7%	12.6%	2.1%	3.4%	3.6%	4.4%
Work	8.6%	8.5%	7.6%	8.1%	8.3%	3.4%	7.0%	7.0%	7.5%	0.9%	1.3%	1.8%	2.2%
Elsewhere	13.8%	12.0%	11.5%	10.9%	10.2%	6.3%	6.1%	7.7%	14.6%	1.9%	2.4%	3.3%	4.4%

at work and elsewhere is increasingly underestimated with a decreasing number of clusters. Taking a closer look at the maximum and mean absolute deviation of the availability of EVs in each defined feature, the deviation of the characteristics from the reference increases for all clustered EV profiles. The extent of the influence of these deviating characteristics on other elements in the energy system is analyzed in Chapter 3.1 to further evaluate the clustered EV profiles.

The clustered EV profiles include discrete EV location and consumption profiles and a share for each EV representative of the total EV number. Consequently, the number of EVs for each discrete EV profile is calculated by multiplying the total number of EVs n_{EVs} with the share of each EV profile:

$$f_{num,EVs} = n_{EVs} \cdot share_{EV} \tag{12}$$

Taking into account the scaling factor $f_{num,EVs}$, the constraining variables and parameters are set by Eqs. (8)–(11). The clustered, discrete EV profiles are published in 18 [18].

Modeling of bidirectionally chargeable EVs with aggregated EV profile

To further reduce the complexity of the optimization problem, we aggregate all initial 1000 EV profiles into one EV location and consumption profile that represents the total EV fleet. The aggregated profile contains shares of EV locations and average consumptions of EVs. This leads to a simplified modeling of bidirectional chargeable EVs, since discrete correlations cannot be mapped.

Fig. 2 illustrates the different modeling of aggregated and discrete EV profiles by showing the minimum and maximum availability of a single EV at home compared to the aggregated EV profiles for an exemplary week. The maximum availability of the discrete EV profile is either one or zero, while the maximum availability of the aggregated EV profile varies between 50% and 95%. The minimum availability is determined by the minimum state of charge at departure (example set to 70%) and the minimum safety state of charge (example set to 30%). For the discrete EV profile, it is either 0%, 30% or 70%, while the aggregated minimum availability varies between 15% and 35%. Modeling discrete EV profiles leads to time-dependent correlations that are neglected by the modeling of aggregated EV profiles. A discrete EV that departs with an SoC over 70% comes back with an SoC depending on the SoC at departure. Using the aggregated EV profiles neglects this correlation, but still considers the overall SoC restrictions for the EV pool by the aggregated minimum availability.

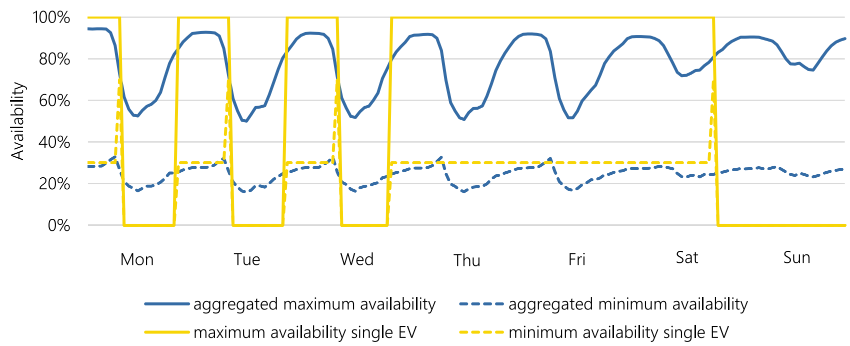

Fig. 2. Different availability of aggregated and discrete EV profiles for an exemplary week.

Since the aggregated profile is normed to one EV, the scaling factor $f_{num,EVs}$ is equal to the number of EVs n_{EVs} as shown in Eq. (13). Again, the constraining variables and parameters are set by Eqs. (8)–(11). The aggregated

EV profiles are published in 18 [18].

$$f_{num,EVs} = n_{EVs} \tag{13}$$

2.2. Integration of V2G applications in the energy system model ISAaR

We use the linear optimization model ISAaR (Integrated simulation model for unit dispatch and expansion with regionalization) that provides a cost-optimal expansion and dispatch of units to model the future European energy system. Fig. 3 illustrates the elements and energy carriers that are modeled in ISAaR. There are multiple elements that couple different energy carriers. Examples are gas-fired power plants or power-to-x technologies that produce other energy carriers from electricity. In addition, storage elements for electricity, heat, hydrogen, and methane provide additional flexibility to the energy system. Energy carriers from outside the geographical scope of ISAaR can be integrated from the model via import. Final energy consumption models provide the energy demand as input data for the optimization. A detailed description of the final energy consumption models Smind EU for the industry sector, TerM EU for the tertiary sector, TRAM EU for the transport sector and PriHM EU for the building sector can be found in Fiedler et al. [19].

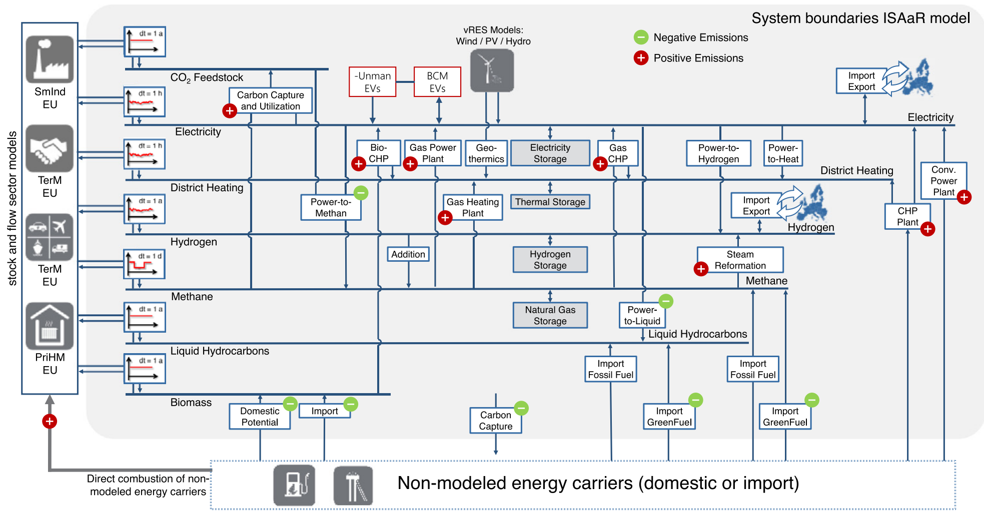

Fig. 3. Illustration of technologies in the multi-energy system model ISAaR and added elements for modeling bidirectionally chargeable EVs.

ISAaR minimized the total energy system costs, while balancing consumption and generation per energy carrier for every timestep and every region. Eq. (14) shows these system constraints. The demand of the final energy consumption sectors for every energy carrier c, every timestep t and every region r P_{demand} is equal to the generation P_{gen} of all elements added to the imports of the energy carrier P_{import} subtracted by the consumption of all elements P_{cons} and the exports of the energy carrier P_{export}. A storage element, such as a bidirectionally chargeable EV, that discharges results in a generation P_{gen} from the energy system's perspective. A storage element that charges represents a consumption from the energy system's perspective. A more detailed description of the ISAaR energy system model can be found in Böing and Regett [20].

$$\begin{gathered} P_{demand}(t,r,c) = \sum_{elements} P_{gen}(t,r,c) - \sum_{elements} P_{cons}(t,r,c) + P_{import}(t,r,c) - P_{export}(t,r,c) \\ for\ every\ timestep\ t,\ region\ r\ and\ energy\ carrier\ c \end{gathered} \tag{14}$$

The final energy demand of the transport sector modeled in TRAM includes the electricity demand of passenger cars for every European country. Since the demand is transmitted to ISAaR statically, TRAM models all passenger cars as unmanaged charging electric vehicles. The integration of bidirectionally chargeable EVs ('BCM-EVs') leads to a decrease in unmanaged charging EVs. Since TRAM provides a static input of electricity demand, the decreasing number of unmanaged charging EVs is modeled by a negative demand '-Unman EVs' reflecting the electrical load of the integrated bidirectionally chargeable EVs. This approach allows a dynamic, model endogenous increase of bidirectionally chargeable EVs in ISAaR. If ISAaR decides to integrate a bidirectionally chargeable EV, this will result in a decrease of the static demand of the transport sector representing a removal of an unmanaged charging EV.

There are two options to integrate bidirectionally chargeable EVs into the energy system model. First, the number of bidirectionally chargeable EVs n_{EVs} can be fixed for future years, meaning a stock element from the model's perspective. Second, bidirectionally chargeable EVs can be modeled as an expansion element with expansion costs. In this case, their number n_{EVs} is endogenously determined by ISAaR. The expansion costs reflect the differential costs of a bidirectionally chargeable EV including EVSE versus an unmanaged charging EV including EVSE.

The described approach for the integration of bidirectionally chargeable EVs in the energy system model can be applied equally for smart chargeable EVs.

3. Results

In the results section we discuss the advantages and disadvantages of the presented modeling approaches of bidirectionally chargeable EVs for an exemplary integration of the EVs in Germany. This is followed by a scenario evaluation of the European energy system with smart and bidirectionally chargeable EVs for the timeframe 2025 to 2050.

3.1. Evaluation of modeling approaches of bidirectionally chargeable EVs

For the evaluation of the different presented modeling approaches, we model the European energy system for the year 2030 with the ISAaR energy system model and integrate bidirectionally chargeable EVs into the German energy system. The parametrization of all modeled elements in the energy system, e.g., generation, consumption, or storage units, is based on the solidEU scenario of the eXtremOS research project. A detailed scenario description of solidEU is published in a summary report [1]. Table 2 shows the parametrization of the bidirectionally chargeable EVs. The EVs are parameterized by a medium passenger car battery capacity of 50 kWh [21].

Table 2. Parametrization of bidirectionally chargeable EVs.

Battery capacity $SoC_{max,1EV}$	Charging/discharging power $P_{c,max,1EV}$ and $P_{d,max,1EV}$	Charging/discharging efficiency η_c and η_d	Minimum safety SoC min_{safe}	Minimum SoC at departure min_{dep}	Location of bidirectional EVSE	Number of bidirectionally chargeable EVs n_{EVs}
50 kWh	11 kW	94%	30%	70%	At home	13 million EVs

The maximum charging and discharging power are set to 11 kW, based on the technical design of the EVSE in the BCM project [4]. The charging and discharging efficiencies of 94% (losses in EV and EVSE included) are the future efficiencies expected by experts from the BCM project [4]. The safety minimum SoC and the minimum SoC at departure are set to 30% and 70%, respectively, and the location of the bidirectional EVSE is at home. The fixed EV number of 13 million EVs is oriented to the underlying solidEU scenario [1].

We evaluate the three different modeling approaches presented in Chapter 2 in regard to differences in simulation results and computing time. The first presented modeling approach of a discrete EV modeling is the most detailed and thus serves as a reference for the other modeling approaches. Table 3 summarizes the impact of the different EV modeling approaches with respect to computation time, EV behavior and repercussions on the energy system.

The discrete EV modeling leads to a computation time of 410 million ticks for the one-year energy system optimization, which corresponds to a computation time of 3 days on the computing servers[1] used. The discrete

[1] Hardware: 2xAMD EPYC 7F52 – 16 Core, 1008 GB RAM Software: Matlab [22], Gurobi Optimization [23].

Table 3. Impact of different EV modeling approaches on computation time, EV behavior and repercussions in the energy system.

Modeling approach	Specification	Computation time (ticks)	EV behavior						Repercussions on the energy system				European modeling as expansion element
			min avail-ability	max avail-ability	mean avail-ability	charge in TWh	dis-charge in TWh	revenues per EV	Overall costs in bn€/a	Wind onshore in TWh in DE	Wind offshore in TWh in DE	PV in TWh in DE	
Discrete EV profiles	1000 EV profiles	410 million	0.49	0.95	0.78	124.4	91.9	158.25	410.40	261.6	185.8	219.3	no
Discrete clustered EV profiles	50 EV profiles	175 million	0.38	1.00	0.80	124.2	95.4	165.51	410.25	261.9	188.5	219.5	no
	20 EV profiles	162 million	0.19	1.00	0.81	124.4	96.2	161.42	410.39	261.8	180.2	227.6	no
	10 EV profiles	157 million	0.11	1.00	0.81	123.1	96.6	163.53	410.37	262.0	178.9	229.0	no
	5 EV profiles	155 million	0	1.00	0.82	120.2	96.0	164.08	410.42	261.8	195.4	227.2	no
Aggregated EV profile	1 EV profile	172 million	0.49	0.95	0.78	125.9	91.7	158.33	410.38	262.2	191.3	231.8	yes

clustered EV modeling results in much lower computation times of 155 million ticks for 5 EV profiles to 175 million ticks for 50 EV profiles. The aggregated EV profile modeling also has a computation time in this range with 172 million ticks. Although in this approach the EVs are modeled with only one profile, the computation time is slightly higher than for the approaches with 5, 10 and 20 discrete clustered EV profiles. This may be due to the more complex aggregated EV profile, but also to the feedback effects of the EV profile on the energy system.

As a second evaluation of the EV modeling approaches, Table 3 shows the EV behavior of the 13 million EVs modeled in the German energy system. The minimum, maximum and mean availability refers to the availability of the EVs at home over all simulated 8760 h of the year. For the EV fleet in Germany, represented by the 1000 discrete EV profiles, the minimum availability is 48%, the maximum availability is 95% and the mean availability is 78%. These characteristics are matched perfectly by the aggregated EV profile. The discrete clustered EV profiles lead to a large error for the minimum availability, especially for 5 to 20 EV profiles. This can lead to unrealistic scarcity situations, where hardly any EVs can interact with the energy system. The charged and discharged energy varies between the modeling approaches, but only by a maximum of 5%. The aggregated EV profile matches the reference very well. The revenues per EV are calculated by the EV energy sold minus the EV energy purchased, times the electricity prices and also vary by a maximum of 5%. Again, the aggregated EV modeling approach matches the reference and thus reflects the EV behavior very well.

Finally, Table 3 shows the repercussions of the modeling approaches on the energy system. The overall costs represent all costs in the European energy system, with a large part of the costs being in the electricity sector. The overall costs in the different modeling approaches vary only slightly, with the aggregated EV profile matching the reference case very well. Furthermore, we evaluate the expansion of volatile renewable energies in Germany (DE). The electricity generated by wind turbines or PV plants varies by maximum 6%. In general, the expansion and generation of wind onshore, wind offshore and PV is well represented by the discrete clustered and aggregated modeling approach.

For a final evaluation of the modeling approaches, one must consider that the modeling will be applied to all European countries in the ISAaR energy system model. Furthermore, we will also evaluate an optimized expansion of bidirectionally chargeable EVs, which brings even more complexity. The modeling approach with 1000 discrete EV profiles already has strong computational time disadvantages when modeling German bidirectionally chargeable EVs and is therefore excluded. The aggregated profile shows slight performance advantages compared to the discrete clustered EV profiles, especially for the EV behavior. A European modeling includes 30 European countries and results in 30 times more EV profiles than in our test simulations. In an optimized integration of bidirectionally chargeable EVs for all modeled European countries, the modeling of an aggregated EV profile resulted in a computation time similar to the test scenario, while the modeling of 5 discrete clustered EV profiles per country already led to 4 times higher computation times. For these reasons, we recommend modeling bidirectionally chargeable EVs with an aggregated EV profile per country to significantly reduce computation time, while still providing a good realistic representation of bidirectionally chargeable EVs.

3.2. Future European energy system with and without V2G applications

To evaluate the integration of smart and bidirectionally chargeable EVs in Europe, we set up a European reference scenario for the years 2025 to 2050 based on the solidEU scenario of the research project eXtremOS. A detailed scenario description of solidEU is published in a summary report [1]. This reference scenario *'Ref'* is characterized by a harmonized decarbonization of the European energy system until 2050. It does not integrate smart and bidirectionally chargeable EVs. For evaluating the value of smart and bidirectionally chargeable EVs, we set up a second scenario *'BCM'* that enables the integration of these EVs. The number of smart and bidirectionally chargeable EVs can be expanded endogenously in every European country using the energy system model. Since there are no European country-specific data for EV profiles publicly available, we use the aggregated German EV profile for every European country. This approach neglects country-specific driving behavior, but considers the weekly and seasonal driving characteristics, which in other European countries do not differ fundamentally from the German characteristics, since working days and working hours are similar in all European countries.

The smart and bidirectionally chargeable EVs are parameterized by the characteristics of a mid-size passenger car described in Table 2. The number of the EVs is endogenously optimized and not fixed by parameters. For this optimized integration, Table 4 shows the additional investment costs of smart and bidirectionally chargeable EVs compared to unmanaged charging EVs. These additional investment costs include additional investments and installation costs for the EVSE and for additional required measuring equipment. The costs do not include additional investment costs for the EV itself. The assumptions for the additional investment costs were made within the BCM research project in consultation with various experts [24]. Currently, only a few offers for bidirectional EVs and EVSEs are available that are consequently high-priced. The only available offer for a bidirectional EVSE in Germany is around 6000 € [25] compared to around 500 € for an unmanaged EVSE [26] resulting in difference costs of 5500 € only for the purchase of the EVSE. Table 4 shows that experts in the BCM research project expect a high cost degression for bidirectional EVSEs in the timeframe up to 2040, when unit numbers in production go up. The lifetime of the smart and bidirectionally chargeable EVs, including their EVSE, is set to 15 years [27] and the interest rate from the energy system's perspective is 3.5% [28]. Both values are needed for the calculation of annual investment costs in the energy system model.

Table 4. Additional investment costs of smart and bidirectionally chargeable EVs compared to unmanaged charging EVs.

	Year	2025	2030	2035	2040	2045	2050
Additional investment costs for EV in €/EV	Smart chargeable EVs	960	760	760	760	760	760
	Bidirectionally chargeable EVs	2840	2190	1890	1590	1590	1590

Fig. 4 analyzes the EV numbers from 2025 to 2050 in a cost-optimized future European energy system in the *BCM* scenario. Supplementary Appendix A presents the exact numbers of EVs per charging strategy per country from 2025 to 2050. In Fig. 4(a), one can see the number of smart and bidirectionally chargeable EVs compared to unmanaged charging EVs. The first thing that stands out is that almost no smart chargeable EVs are added endogenously by the energy system model. This means that the added value of bidirectionally chargeable EVs to the energy system significantly exceeds the additional costs of these EVs, when costs are considered as shown in Table 4. The number of integrated bidirectionally chargeable EVs goes up from 7 million EVs in 2025 to 62 million EVs in 2050 and has the highest share in 2045 of 37%. This significant increase indicates that the future European energy system becomes more efficient with the provided flexibility through bidirectionally chargeable EVs.

Fig. 4(b) shows the integration of bidirectionally chargeable EVs in the six countries Germany (DE), Spain (ES), France (FR), Italy (IT), Poland (PL) and United Kingdom (UK) representing the European countries with the highest number of integrated EVs. The increase in bidirectionally chargeable EVs is not occurring equally in different countries, but rather has characteristic differences. In Spain and Italy, the energy system model already integrates around 2 million bidirectionally chargeable EVs in 2025, significantly more than in the other countries displayed. As of the year 2035, the countries Germany, France and Italy have the most bidirectionally chargeable EVs. In 2050 in Germany there is a sharp decrease in bidirectionally chargeable EVs, meaning that some of the previous bidirectionally chargeable EVs that reached their lifetime are replaced by unmanaged charging EVs. In 2050 in Germany, expanded hydrogen-fired power plants provide flexibility leading to a lower flexibility needed on the demand-side.

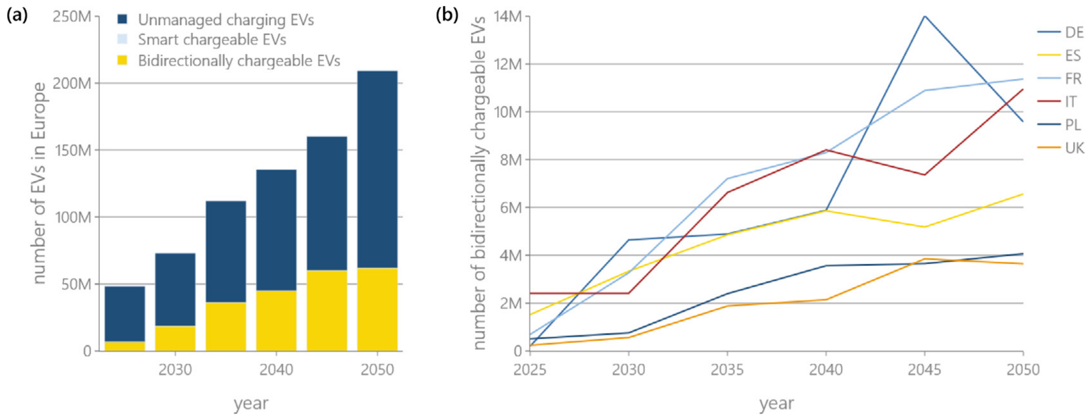

Fig. 4. Analysis of future EV numbers from 2025 to 2050 in a cost-optimized European energy system: (a) total EV number per charging strategy; (b) integrated bidirectionally chargeable EVs per country.

If unmanaged charging EVs are replaced by bidirectionally chargeable EVs, the EV loads due to additional equivalent full cycles (EFCs) of the battery will be increased. The EFCs of bidirectionally chargeable EVs are highest in 2025 at 280 EFCs/a, going down to 200 EFCs/a in 2035 and 185 EFCs/a in 2050 compared to approximately 60 EFCs/a for an unmanaged charging EV with 50 kWh battery capacity.

For a more detailed European evaluation of the integration of bidirectionally chargeable EVs, Fig. 5 analyzes the shares and numbers of EVs per charging strategy per country in 2030 and 2050. As additional information, the coloring of the countries is related to the full load hours of PV generation. In 2050, there are both higher numbers of EVs and higher shares of bidirectionally chargeable EVs in most countries compared to 2030. The integrated shares of bidirectionally chargeable EVs are much higher in most southern European countries compared to the northern European countries. It is noticeable that the share of bidirectionally chargeable EVs is higher in the countries that have higher full load hours of PV generation. This dependence can be explained by the fact that bidirectionally chargeable EVs often act as daytime storages. The parameterized EVs have an energy/power ratio of 50 kWh/11 kW. This means they can charge or discharge for a maximum of four and a half consecutive hours. The PV generation

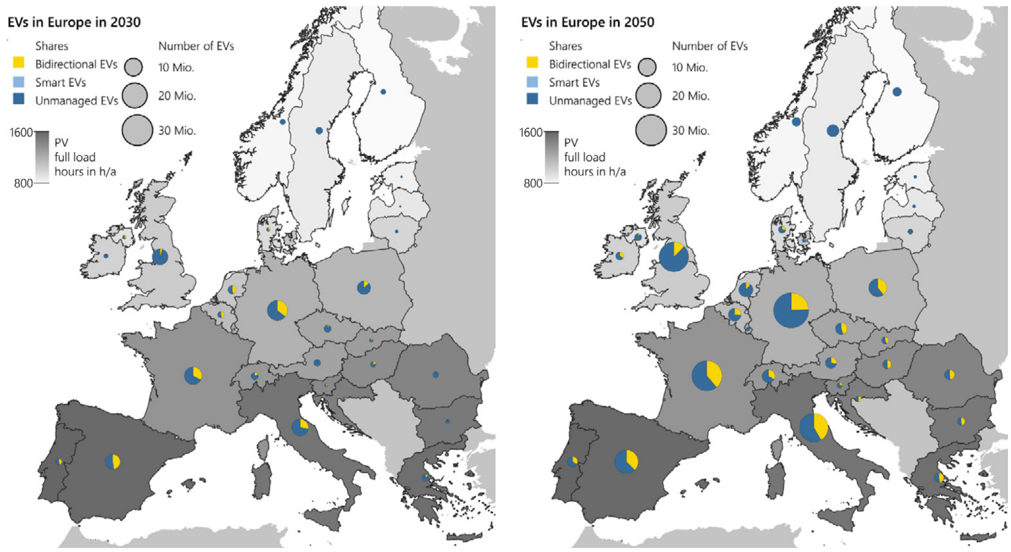

Fig. 5. Dependence of shares and numbers of EVs per charging strategy per country in 2030 and 2050 on the full load hours of PV generation.

represents a regular daily generation profile with only seasonal differences. Therefore, bidirectionally chargeable EVs can provide the necessary flexibility to more evenly feed-in the PV generation into the energy system. Higher full load hours of PV generation indicate a more cost-effective expansion of PV generation and thus indicate a more attractive location for bidirectionally chargeable EVs.

As a detailed scenario comparison, Fig. 6 shows the capacities of conventional power plants, volatile renewable energies, and storage technologies for the scenarios *Ref* and *BCM* for the years 2030, 2040 and 2050 in Europe. The analysis points out structural differences, but also similarities, in the future European energy system. There is a high increase in all volatile renewable technologies in future years due to the ongoing decarbonization of the energy system. However, there are some differences between the installed capacities of renewable energies in the scenarios *Ref* and *BCM*. In general, the *BCM* scenario prefers an expansion of PV generation compared to an expansion of wind onshore and wind offshore generation. Bidirectionally chargeable EVs act as a daytime storage increasing the consumption at the time of peak PV generation and thus raise the market value of PV generation. Therefore, bidirectionally chargeable EVs are an incentive to the integration of PV generation that is the volatile renewable energy source with the lowest levelized cost of electricity in ISAaR.

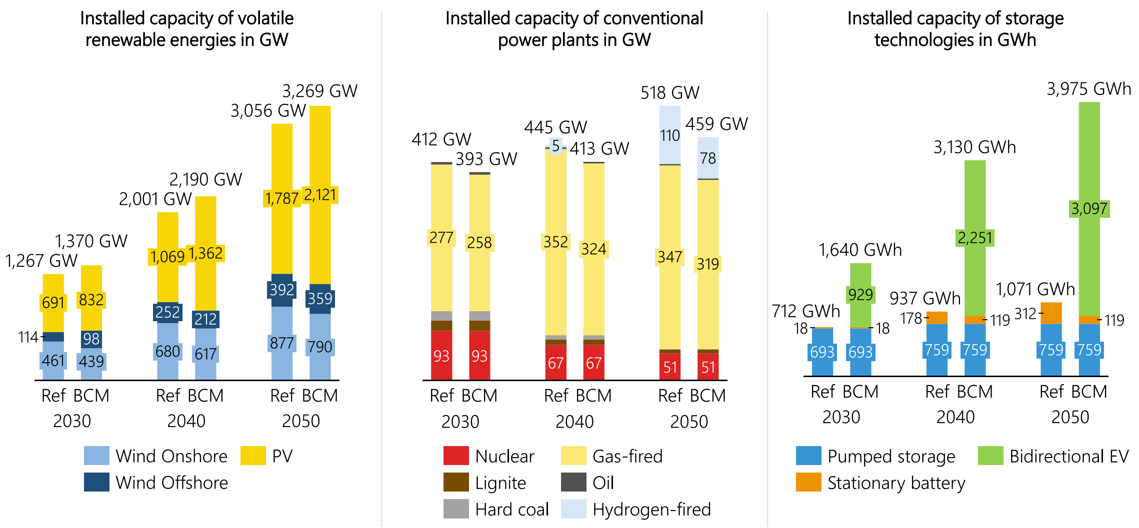

Fig. 6. Installed capacities of conventional power plants, volatile renewable energies, and storage technologies for the scenarios *Ref* and *BCM* for the years 2030, 2040 and 2050 in Europe.

The installed capacities of conventional power plants increase from 2030 to 2050, although the full load hours and thus the electricity output decreases by over 50%. PV plants and wind turbines are characterized by a fluctuating electricity generation that leads to a higher demand of conventional power plants as back-up capacities. The gas-fired power plants in 2050 generate electricity with synthetic methane produced by renewable energies. When comparing the two scenarios *Ref* and *BCM*, it is noticeable that less gas-fired and hydrogen-fired power plant capacity is expanded in the BCM scenario. Bidirectionally chargeable EVs discharge and thus feed-in electricity into the energy system when there is a high need for electricity generation due to a high consumption or a low generation or both. Consequently, gas- or hydrogen-fired power plants can lower their electricity generation in these situations. Therefore, from the energy system's perspective, bidirectionally chargeable EVs lead to a decreased need for flexible gas- and hydrogen-fired power plants.

The installed capacity of storage technologies increases significantly from 2030 to 2050 in both considered scenarios. In the reference scenario *Ref,* the only storage expansion option for the energy system model is the increase of stationary battery storages. The BCM scenario has the expansion options of stationary battery storages and bidirectionally chargeable EVs. Pumped storage hydropower is set fixed for future years and cannot be endogenously expanded. The *BCM* scenario clearly favors the integration of bidirectionally chargeable EVs over the expansion of stationary battery storages. The lower investment costs of bidirectionally chargeable EVs compared to stationary battery storages outweighs the disadvantage of limited availability of EVs. In terms of one MWh of storage capacity, bidirectionally chargeable EVs have investment costs of 31,800 € in 2050 compared to stationary battery storages that cost around 123,000 € in 2050 based on eXtremOS project [29]. These cost advantages outweigh the limited availability of the EV's storage capacity due to the connection status of the EV to the EVSE and minimum SoC constraints because of the user behavior. These results show that bidirectionally chargeable EVs significantly lower the need for other storage technologies in a cost-optimal future European energy system.

For the analysis of electricity prices, Fig. 7 shows the sorted hourly electricity prices in Italy (IT) and the United Kingdom (UK) as exemplary countries with a high and a low share of bidirectionally chargeable EVs for the years 2030 and 2050 for both scenarios *Ref* and *BCM*. In general, the *Ref* scenario results in a slightly higher sorted electricity price curve. Bidirectionally chargeable EVs in the *BCM* scenario charge when electricity prices are low, resulting in a partly electricity price increase of the low prices. On the other hand, they discharge when electricity prices are high, leading to a partly decrease of the highest electricity prices. These effects result in an overall smoothing of the electricity prices. Italy has a much higher share and number of bidirectionally chargeable EVs than the United Kingdom. Consequently, the impact of the bidirectionally chargeable EVs on the electricity price is also higher in Italy compared to the UK. But while the share of bidirectionally chargeable EVs in the UK, at 6% in 2030 and 12% in 2050, is comparably low, the impact on electricity prices is nevertheless strongly recognizable.

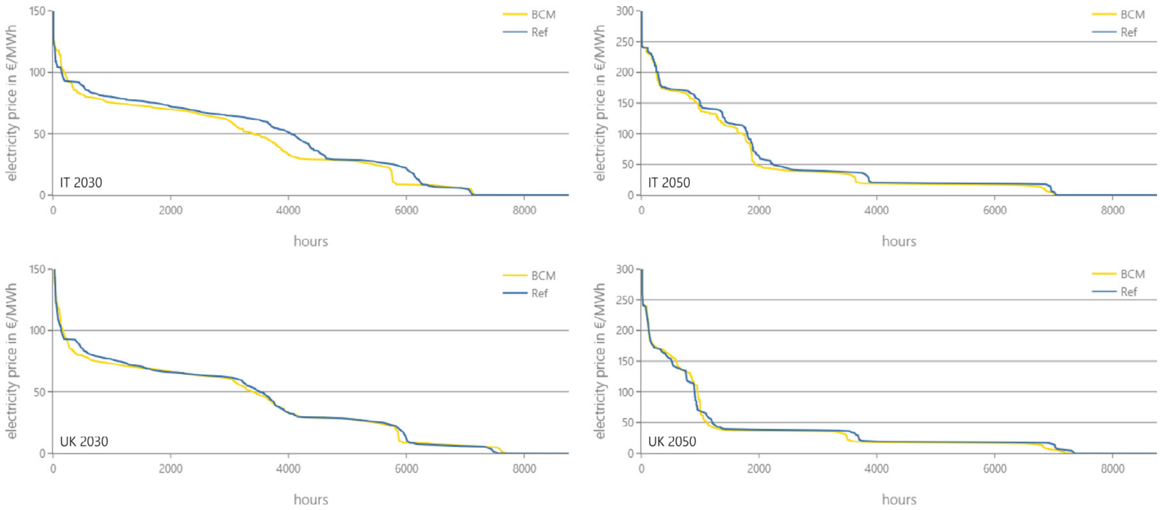

Fig. 7. Sorted hourly electricity prices in Italy (IT) and the United Kingdom (UK) for the years 2030 and 2050 for both scenarios Ref and BCM.

The difference in the design of the energy system between the scenarios *Ref* and *BCM* leads to a difference in overall energy system costs and mean electricity prices. Table 5 summarizes these key indicators for both scenarios for the years 2025 to 2050. The mean European electricity price is calculated by the demand-weighted electricity price over all modeled European countries and timesteps. Bidirectionally chargeable EVs cause a decrease in electricity prices by up to 12% in 2040. Renewable energies are better and more cost-effectively integrated into the energy system, thus the use of expensive thermal power plants is reduced. The overall energy system costs are

Table 5. Overall energy system costs and mean European electricity price for the years 2025 to 2050 for scenarios *Ref* and *BCM*.

Year	Overall energy system costs in billion €/a		Mean European electricity price €/MWh	
	Ref	*BCM*	*Ref*	*BCM*
2025	432.4	431.7	44.6	42.6
2030	414.6	412.4	42.5	39.4
2035	354.9	350.1	43.1	39.1
2040	332.2	325.7	44.6	39.4
2045	323.5	314.4	44.4	41.1
2050	353.1	345.0	41.6	38.8

also reduced. While total energy system costs are only slightly lower in *BCM* than in *Ref* in 2025, costs decrease by over 9 billion €/a in 2045. Reduced costs on the power supply side clearly outweigh the additional investment costs of bidirectionally chargeable EVs.

4. Discussion

Bidirectionally chargeable EVs represent an essential component of the future energy system. In this study, we analyze different modeling approaches of bidirectionally chargeable EVs in a complex multi-energy system model and evaluate their integration as well as their impact on the European energy system in future years. For complex energy system models, we recommend the modeling of one aggregated EV profile to limit computation time, while modeling a realistic representation of the EV composition of a country. We show numerous positive effects of bidirectionally chargeable EVs:

- Bidirectionally chargeable EVs support the integration of PV generation. This is of great importance for the future energy system, since wind generation, especially onshore wind generation, deals with various acceptance issues across Europe [30].
- Bidirectionally chargeable EVs lower the required installed capacities of conventional power plants, such as gas- or hydrogen-fired power plants. Replacing the need for power plant capacities that operate with very few full load hours through bidirectionally chargeable EVs means contributing to the security of supply of the energy system.
- Bidirectionally chargeable EVs lower the required installed capacities of other storage technologies, such as stationary battery storages, and thus cause a lower demand of battery capacities.
- Overall energy system costs and electricity prices decrease with an integration of bidirectionally chargeable EVs, which makes the European energy system more cost-efficient and results in lower costs for the end user of electricity.

Therefore, our results support studies from Hanemann et al. [10], Rodríguez et al. [11], Wei et al. [13], Child et al. [14] that already showed positive impacts of smart or bidirectionally chargeable EVs on local energy systems. We further show interrelated effects in the coupled European energy system, discuss different detailed modeling approaches of bidirectionally chargeable EVs in a large-scale energy system model and finally output cost-optimal penetration rates of bidirectionally chargeable EVs in the future European energy system.

However, there are some limitations of the modeling and the results that show the need for further research. The aggregated EV profile is based on German mobility data of passenger cars. More detailed mobility data of other European countries could have an influence on repercussions in the energy system. However, the basic findings should not be affected. The effect of the parametrization of the EVs, including investment costs for smart and bidirectionally chargeable EVs, should be investigated further. Possible larger EV battery capacities in the future could even increase the added values of bidirectionally chargeable EVs.

The additional load on EVs through bidirectional charging is high. 200 EFCs per year in 2035 with a lifetime of 15 years result in a total of 3000 EFCs for the EV battery capacity. However, comparing these EV loads to current EFC lifetime values for station battery storage systems that are around 5000 EFCs [31,32] suggests that these EV loads will be sustainable in the future.

The ISAaR energy system model optimizes the European energy system in an hourly annual simulation. Each European country represents one node. The European transmission grid is only modeled by cross border transfer capacities between countries, while the distribution grid is not modeled. Therefore, the impact of bidirectionally chargeable EVs on grid utilization is not addressed by this study and should be further investigated. Due to the high simultaneity of EV charging or discharging operations with market-driven use of EVs, there is a risk of grid overloading. Müller et al. [33] already deal with the impact of smart and bidirectionally chargeable EVs on the distribution grid utilization and show decreasing and increasing grid overloads dependent on the use case and the charging strategy.

Finally, the results of the future cost-optimized energy system shown in Chapter 3.2 are from the perspective of the energy system and not from the perspective of the users. Consequently, there are no fees and taxes on electricity prices modeled that could change the dispatch of storage units, like bidirectionally chargeable EVs.

5. Conclusion

To evaluate the impact of electric vehicles (EVs) on the future European energy system, we analyze modeling approaches of smart and bidirectionally chargeable EVs in a large-scale multi-energy system model and model the future European energy system with and without the option of integrating these EVs. We show that aggregated EV profiles per country are sufficient to realistically model the EV behavior and the repercussions on the energy system. We find future cost-optimized penetration rates of bidirectionally chargeable EVs per country from the energy system's perspective, and thus support stakeholders in the industry in planning their future business models. Furthermore, we encourage policy makers to enable bidirectional charging of EVs through regulatory measures in order to realize the presented positive impacts on the energy system. Finally, the paper is intended to support scientists by providing detailed descriptions of modeling approaches of bidirectionally chargeable EVs and data of EV profiles.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.egyr.2022.10.277.

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