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Quantification of the Flexibility Potential through Smart Charging of Battery Electric Vehicles and the Effects on the Future Electricity Supply System in Germany

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Abstract: Electrification offers an opportunity to decarbonize the transport sector, but it might also increase the need for flexibility options in the energy system, as the uncoordinated charging process of battery electric vehicles (*BEV*) can lead to a demand with high simultaneity. However, coordinating *BEV* charging by means of smart charging control can also offer substantial flexibility potential. This potential is limited by restrictions resulting from individual mobility behavior and preferences. It cannot be assumed that storage capacity will be available at times when the impact of additional flexibility potential is highest from a systemic point of view. Hence, it is important to determine the flexibility available per vehicle in high temporal (and spatial) resolution. Therefore, in this paper a Markov-Chain Monte Carlo simulation is carried out based on a vast empirical data set to quantify mobility profiles as accurately as possible and to subsequently derive charging load profiles. An hourly flexibility potential is derived and integrated as load shift potential into a linear optimization model for the simultaneous cost-optimal calculation of the dispatch of technology options and long-term capacity planning to meet a given electricity demand. It is shown that the costs induced by *BEV* charging are largely determined by the profile costs from the combination of the profiles of charging load and renewable generation, and not only by the additional energy and capacity demand. If the charging process can be flexibly controlled, the storage requirement can be reduced and generation from renewable energies can be better integrated.

Keywords: electricity sector; flexibility; electric mobility; demand side integration; total system costs; decarbonization

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1. Introduction

In order to achieve climate targets specified in international agreements, countries set emission reduction targets and action plans in all sectors [1]. The strong expansion of renewable energies plays an important role for the target achievement, but also the rise of the electrification of the heat supply and the mobility sector [2] which, however, leads to a higher electricity demand. Therefore, a more fluctuating feed-in has to meet a demand which is varying in time and space, which increases the need for flexibility [3]. As a result, new problems arise for the dimensioning of the necessary grid infrastructure or generation and storage capacities.

The integration of technologies for sector integration, such as heat pumps or battery electric vehicles (*BEV*), and the use of direct load control, e.g., for charging vehicles, are options to provide flexibility and therefore should be part of the solution. Their actual flexibility potential, however, is subordinated to given boundary conditions from reality. For *BEV* in particular, there are restrictions resulting from individual mobility behavior. The batteries of electric vehicles cannot be assumed as a large storage capacity available at times when impact of additional flexibility potential is highest from a systemic point of view. An efficient use of flexibility options can reduce the need for additional technology investments and thereby the costs for the electricity supply.

The question arises: how can the demand and the flexibility potential of *BEV* be determined adequately based on empirical mobility data? Subsequently, the impact of the use of an intelligent charging control on total system costs as well as on necessary generation capacities has to be analyzed in order to quantify the effects within a systemic evaluation. Empirical household mobility data, which, amongst others, include duration, start and ending location as well as standing times, are available for Germany provided from the Federal Ministry of Transport and Digital Infrastructure (BMVI) [4]. The key findings of the study, in which the data collection was conducted, are presented in [5], while a more detailed overview on the data can be found in [6]. Taking only the averages of all rides in the data leads to a mobility pattern which does not reflect the variety of individual mobility needs and therefore additional assumptions to subsequently derive realistic charging profiles are necessary. In [7], for example, a clustering is used to construct representative driving patterns based on historical data. Data-samples on real charging behavior are published in several studies and research projects and often used to derive only generic load profiles, as is done in [8].

The flexibility potential based on charging curves can be determined with several methods and can be described differently. The timeframe of the use of the flexibility of BEV can be considered as short-term when it is compared with the definition in [9], because the mobility is assumed to have a daily pattern with its resulting restrictions. Approaches for modeling differ fundamentally in whether Vehicle-to-Grid (*V2G*) is enabled or only the pure shifting of the loading process is considered. In addition, further boundary conditions can be assumed, such as blocking times during which the charging process cannot be postponed or a minimum charge level of the vehicle. In the literature, the willingness of *BEV* owners to allow external access at all as well as possible financial incentives, which would be necessary, is discussed [10].

Above all, in the optimization of the renewable self-consumption or the net purchase, intelligent load strategies play a large role in the future. Partly they are already implemented in real demonstrators (for example in [11]) and are part of research (for example in [12]) as well as being implemented in reality. In many cases, a fixed electricity price curve is specified, the own consumption is maximized or the peak of the power supply is minimized. The use of flexibility to stabilize the power grid is also investigated and can be useful if sufficient knowledge of the locally available potential is available. For example in [13], optimal operation points of an existing network are identified using a Monte Carlo simulation under consideration of a given load (including *BEV*) and renewable energy production. These local analyses often neglect interaction with the rest of the energy system and therefore don't have a focus on future effects on the energy system regarding capacity expansion.

In analyses for the long-term planning of the energy system, the effects of increasing electrification of the transport sector on the energy system have already been analyzed, e.g., in [14]. The amount of energy required for motorized private transport and freight transport is determined and integrated into the respective model by means of a load curve. The studies differ in the spatial resolution or other aspects as well as the system boundary and the level of detail in the transport sector. Research studies focus, amongst other factors, on the necessary grid extension [15] or impacts on household prices [16] on an actor's perspective by a rising penetration of *BEV*. Effects on a systemic level concerning the flexibility use in high temporal resolution, the necessary capacity investments and the resulting system cost components are not analyzed extensively with a focus on *BEV*. The difficulty in all these investigations remains, however, to determine the individual mobility behavior in general in order to determine a realistic availability of flexibility and to quantify the benefit in interactions with the dynamic energy system.

Therefore, this paper presents an approach to adequately determine the load profiles and the flexibility potential of *BEV* and their integration, as well as its use, within an electricity market model. The question of the optimal technology mix for cross-sectoral decarbonization of the energy system is not the focus of attention.

2. Materials and Methods

In the given paper, a methodology is presented to adequately determine the flexibility potential of BEV and to calculate its use within an electricity market model considering feedback effects. BEV-specific input data are determined based on empirical mobility data for Germany within a mobility tool. In this tool, mobility profiles per car are determined using a Markov-Chain Monte Carlo simulation. Based on these profiles, the resulting load curve of BEV's, and subsequently the flexibility potential, is determined as input for the electricity market model. In order to evaluate the benefits of a flexibilization of the BEV charging process by demand side integration (DSI), we determine the flexibility requirements and calculate total system costs in a scenario with ambitious climate targets with the electricity market model in which different technologies and flexibility options are implemented. An overview of the methodology is shown in Figure 1. The mentioned boxes and its key points, listed under the headlines "(EV-)Mobility Simulation Tool" (Empirical Mobility Data, Mobility Profiles, BEV Charging Profiles, Flexibility Potential of intelligent BEV-charging) and "Electricity Market Model E2M2", are addressed in more detail in the following methodology presented in this section.

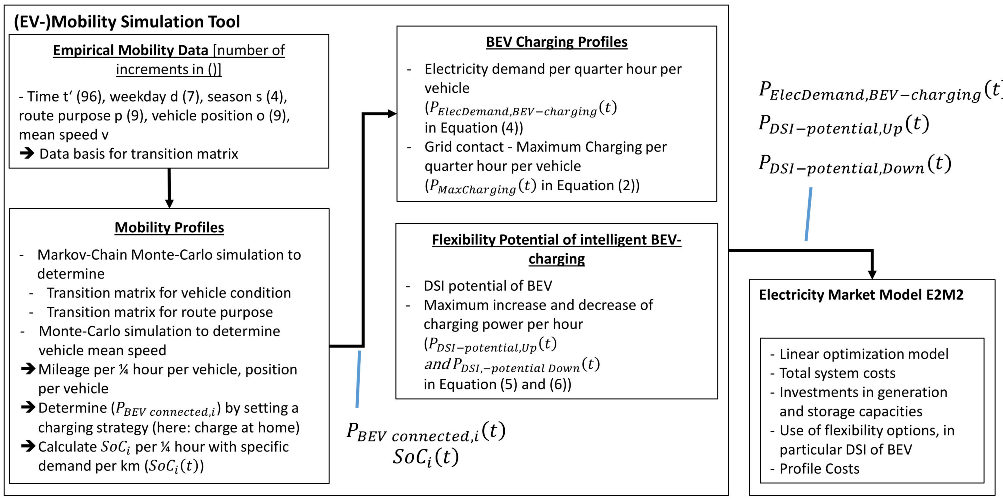

Figure 1. Overview of the approach presented in this paper.

2.1. Determination of Mobility and Load Curves

An empirical data set on the mobility behavior of private individuals in Germany with more than 316,000 respondents is available as the basis for determining mobility profiles [4]. It contains, amongst others, information on the time of departure, the purpose of the journey, the duration of the journey and the standing times in a quarter-hourly resolution. Based on these data, transition probabilities are determined in order to use them in a Markov-Chain Monte Carlo simulation and thereon develop mobility curves.

A probability for the vehicle status results from the sum of the trips at the respective point in time and the following driving status in the next time segment. The stochastic process of the time a vehicle starts to arrival at its destination can be reduced to the states "en route" or "standstill" and described as solely dependent on the initial state for every time step. Following [17], it can subsequently be modelled as a discrete-time stochastic process $(X_n)_{n \epsilon N0}$ with finite state space Z and is called a Markov Chain if it satisfies the Markov property, i.e., if the following holds:

$$P(\{X_{n+1} = Z_{n+1}\}|\{X_0, \ldots, X_n) = (z_0, \ldots, z_n)\}) = P(\{X_{n+1} = Z_{n+1}\}|\{X_n = z_n\}) \quad (1)$$

For all $n \in N$ and $z_0, \ldots, z_{n+1} \in Z$ with $P(\{(X_0, \ldots, X_n) = (z_0, \ldots, z_n)\}) > 0$ [18].

The conditional probability $P(\{X_{n+1} = Z_{n+1}\}|\{X_n = z_n\})$ is called the transition probability from the state z at time n to the state z at time $n+1$. Each theoretically possible state at time $n+1$ is assigned a transition probability depending on all possible initial states at time n. These transition probabilities can be summarized in a quadratic matrix, which is called a transition matrix [18].

Such transition matrixes are generated for every time step and state using the vast data set of MiD 2017, which comprises empiric mobility profiles of 25,922 households with, in total, 60,713 persons and 193,290 routes. The Markov-Chain Monte Carlos simulation is used based on the transition matrix for the vehicle conditions depending on the time-step (96 quarter hours per day), the weekday (7 days), the season and the last route's purpose (9 different purposes). An example of such a transition matrix for the cars condition is given in Table 1.

Table 1. Structure of the transition matrix for the condition of the car with exemplary entries.

Season	Weekday	Time Step	Last Routes Purpose	Initial State	Final State		Σ
					En Route	Standstill	
...	...	...	...	en route	...		1.00
				standstill			1.00
Autumn	Monday	7:00 to 7:15	...	en route	0.93	0.07	1.00
				standstill	0.00	1.00	1.00
...	...	...	...	en route	...		1.00
				standstill			1.00

The implementation of the simulation is described in detail by [17]. The advantage of this procedure is that each of the single runs recorded in the data set are taken into account to determine the transition matrix and therefore the synthetic motion profiles. For every car, the current status and the initial state of the car leads to the probability of the transition matrix for the next time step, the final state of each simulation.

Following this concept, another transition matrix is created based on the empirical data to aquire the probabilities for the purpose of the route when the car's status is changing from "standstill" to "en route". The purposes of the route include, for example, "way to work", "leisure" or "drive home". The data set includes a total of 9 purposes, which are dependent on the season and the weekday. An example for the transition matrix for the route purposes is given in Table 2.

Table 2. Structure of the transition matrix for the route purposes of the car with exemplary entries.

Season	Weekday	Final State (9 Route Purposes)				Σ
		Way to Work	Leisure	...	Drive Home	
...	...		...			1.00
Autumn	Monday	0.23	0.17	...	0.12	1.00
...	...		...			1.00

The Markov-Chain is processed for each of the assumed cars within the Monte Carlo simulation until the result converges again to the expected value.

Furthermore, the vehicle mean speed $v(t)$ is determined by means of a conditional probability distribution of vehicle mean speed depending on the time, weekday and season in the same way using a Monte Carlo simulation. As a result of the simulation, we get the information about the mileage per quarter hour and the position per hour. Assuming a specific demand per km, we get the energy consumption and so the state of charge (SoC)

per car and quarter hour. Consumption only occurs if the vehicle condition is declared as “en route”.

If the state of the car changes to “standstill” and “at home” in the next time step, the car is stated to be connected to the grid as a specific user behavior, and immediate uncontrolled charging at home after each journey is assumed. The sum of all cars’ simulation results leads to the mobility profile and the charging profile from *BEV*. In the following equations to describe the interface between the mobility simulation and the optimization model, parameters are annotated with “*P*”, and variables with “*V*”. By aggregating the quarter-hourly simulation results for each hour *t*, the maximum charging power of all connected cars, which is further referred to as the “grid contact curve” can be described by

$$P_{MaxCharging}(t) = P_{BEV\ connected}(t) * P_{charging\ capacity} \quad (2)$$

A charging infrastructure with a charging capacity of 3.7 kW, as installed in most households, is assumed [19]. The charging process in the simulation tool starts with maximum power until the vehicle is fully charged. The number of charging car at each time step can be described by

$$P_{BEV\text{-}charging}(t) = \sum_i P_{BEV\ connected,i}(t) \mid i \text{ with } SoC_i < SoC_{max} \quad (3)$$

An initial state of charge of the batteries based on the final state of the previous day is also taken into account. Within the tool other options, e.g., charging at work, are possible but not part of this study.

The consumption of the cars, the connection to the grid and the charging capacity results in the user controlled charging-curve of all *BEV* for each time step and is stated by

$$P_{ElecDemand,BEV\text{-}charging}(t) = P_{BEV\text{-}charging}(t) * P_{charging\ capacity} \quad (4)$$

In the work presented here, the mobility data are summarized for the core week from Monday to Thursday and for each season to reduce complexity. Further on, the Monte Carlo simulation is processed 750 times (which corresponds to 750 vehicles) to reach a high statistical accuracy of results while having a tolerable calculation time. Within a season, the mobility behavior for a Friday, for example, is always assumed the same. This results in a typical week for each season, which describes all weeks in this season. By aggregating all seasons, the course for a whole year is then obtained.

At the moment, Germany mainly has vehicles with combustion engines and thus these also form the basis for the majority of data on mobility behavior. For the derivation of the charging curve of *BEV*, it is assumed that the mobility requirements and user behavior will remain the same in the event of a greater penetration of electric vehicles in the future. Therefore, we use the current mobility behavior data for combustion engines for our mobility demand calculation without considering different user types.

A representative *BEV* is assumed for the calculation of the load curve. The specific consumption and battery capacity is calculated by quantity weighting for each vehicle segment and the electric vehicles newly registered in Germany. The data and the derivation of a typical *BEV* are given in the Appendix A.

2.2. Determination of the Flexibility Potential of Intelligent Charging Control

To determine the flexibility potential of an intelligent charge control, further assumptions are made. The use of *V2G* is excluded, since the technology is currently still in the experimental stage and no solutions have yet been found regarding the compensation payment for the expected reduction in service life due to aging of the batteries as a result of the additional number of cycles. Furthermore, it is assumed that the charging capacity can only be postponed to a later point in time, since every vehicle is charged in uncontrolled mode immediately after plugging in. A shifting forward of the load would be possible in regard to the aggregated charging curves, but does not reflect the results of the modeling and the spatial distribution of the cars in reality.

The goal is to describe and quantify the load shift potential based on the determined load curves. For this purpose, a range of the maximum possible load is defined, which corresponds to the power of all vehicles with full power supply connected at that time: the grid contact curve. It includes vehicles that are already fully loaded and currently not receiving any power. The difference between the maximum possible charging power $P_{MaxCharging}(t)$ (the grid contact curve) and the actual charging power at a given point in time $P_{ElecDemand,BEV\text{-}charging}(t)$ corresponds to the positive flexibility potential through power increase ($P_{DSI\text{-}potential,Up}(t)$), as shown in Equation (5).

$$P_{DSI\text{-}potential,Up}(t) = P_{MaxCharging}(t) - P_{ElecDemand,BEV\text{-}charging}(t) \quad (5)$$

This is also referred to as "*PowerUp*" or "*PowerUp-Potential*" in the following. The negative flexibility potential $P_{DSI\text{-}potential,Down}(t)$ results from the difference between the actual charging power and the zero line, no charging process, therefore called "*PowerDown*" or "*PowerDown-Potential*".

$$P_{DSI\text{-}potential,Down}(t) = P_{ElecDemand,BEV\text{-}charging}(t) \quad (6)$$

The relation is also depicted in Figure 2. It shows the maximum possible charging and the realized charging as well as the possible increase or decrease of the process by specifying the PowerUp or PowerDown for an exemplary day, each normalized to the grid contact of all vehicles.

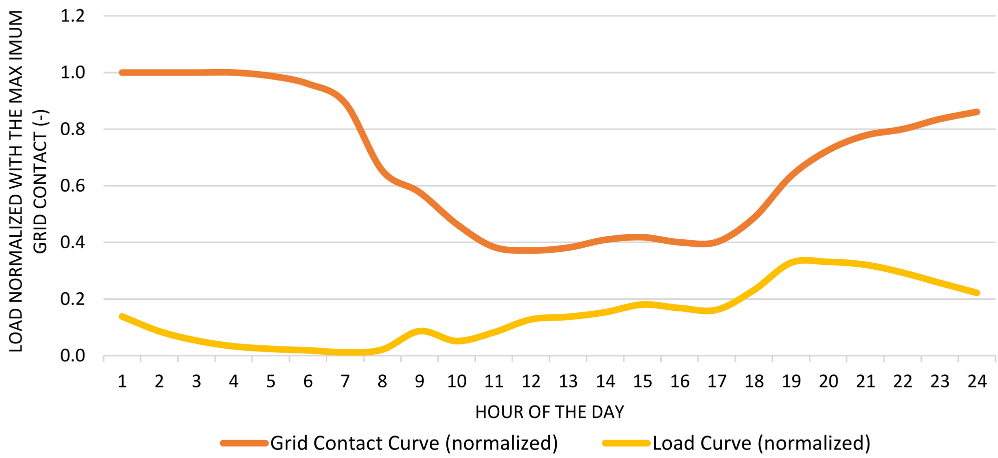

Figure 2. Depiction of the simulated realized charging profile for an exemplary day (yellow line), the maximum possible charging of all cars connected to the station (orange line), the maximum positive flexibility (blue arrow) and maximum negative flexibility (black arrow), normalized values.

As a further assumption to limit the flexibility potential, a maximum duration of the shift is given. We assume that owners of electric cars are willing to allow external access to control their vehicles if they are not restricted in their everyday life. An important point here is the specification of a time at which the vehicle is fully or partially charged. Therefore, the present model of the flexibility potential also specifies a point in time when all vehicles must be fully loaded.

Since the mobility curves are determined based on historical data from moving vehicles and the part of the vehicle fleet that is not moved (on average 41.2%) on a day is not included, the actual demand is overestimated (of about 72.3%) in the modeling when the number of simulated vehicles is scaled to the existing fleet. The average mileage of the vehicles in the given data [4] is 24,054 km and is thus significantly higher in comparison to literature data (13,931 km in 2017 [20]). Therefore, the average mileage of the empirical data is scaled to the average mileage of a passenger car and thus the load demand is reduced accordingly.

2.3. Implementation in the Linear Optimization Model

To work out the effects of an intelligent charge control of *BEV* in a nearly decarbonized energy system with a high share of renewable energies and to analyze the interaction and feedback with other parts of the energy system, the hourly charge performance curves and the flexibility potential are integrated in the electricity market model E2M2 (European Electricity Market Model). It is used to quantify the system effects of the additional flexibility potential created by the intelligent control of the *BEV* charging process.

The model, based on [21], simultaneously optimizes the necessary investments in power plant capacity and flexibility options and their use to meet a given electricity demand in hourly resolution while minimizing the total system costs C_{total}. The objective function includes fixed costs, such as annualized investment costs (C_{Invest}) or annual operating costs (C_{fixOaM}), as well as variable costs (Operation and Maintenance (C_{varOaM}), Fuel (C_{Fuel}), StartUp ($C_{StartUp}$)) for power plant deployment, as shown in Equation (7).

$$C_{total} = C_{Invest} + C_{fixOaM} + C_{varOaM} + C_{StartUp} + C_{Fuel} \tag{7}$$

The electricity demand specified in the model must be met at every hour (see Equation (8)). Various technology options, which are subject to specific techno-economic restrictions, are available for this purpose. In addition to feed-in from renewable energies and conventional power plants, the balance can also be covered by imports or excess electricity can be exported. The production of renewable energy is, different than described in [21], based on a discrete synthetic profile, as it is described in [22]. Furthermore, a temporal offset of the energy demand can be achieved by storages or load management ($V_{DSI,up}$, $V_{DSI,down}$), which are subject to restrictions across time steps. The entire demand equation for each time step then results in:

$$\begin{aligned} P_{ElecDemand} = {} & V_{ElecProduction,conventional} + V_{ElecProduction,renewable} - C_{curtailment,renewables} \\ & + V_{ElecProduction,storages} - V_{Pumping,storages} + V_{DSI,down} - V_{DSI,up} + V_{Import} - V_{Export} \end{aligned} \tag{8}$$

In addition, framework conditions, such as minimum shares of renewable energies or a CO_2-limit, can be taken into account and, depending on the issue at hand, various flexibility options or sector-integrating technologies, e.g., for heat supply, can be considered. The possible flexibility options are described in [23].

Electric mobility is incorporated into the model on the one hand via the load profile determined in the model and on the other hand via the resulting demand-side flexibility. Therefore, the implementation of load management according to [24] is used. The possibility of using load management results from the short-term reduction of the load and thus reduction of demand. The reduced demand has to be covered after a period of time or up to a point in time, depending on the specification. In any case, it must be balanced energetically, which may only be done after the load shift. In the case of electric mobility, in order not to cause a loss of comfort for the *BEV* drivers, it is assumed that the vehicles must be charged at a uniform time. This time is determined after the analysis of the mobility data.

The maximum positive or negative available shifting power is limited by a given hourly potential $P_{DSI\text{-}potential,Down}(t)$ and $P_{DSI\text{-}potential,Up}(t)$ (Equations (9) and (10)). The potential limitation is derived by the procedure described above (see Equations (5) and (6)).

$$V_{DSI,down}(t) \leq P_{DSI\text{-}potential,Down}(t) \text{ and} \tag{9}$$

$$V_{DSI,up}(t) \leq P_{DSI\text{-}potential,Up}(t) \text{ with } V_{DSI,j}(t) \geq 0 \mid j \in down, up \tag{10}$$

The amount of energy shifted by the realized load reduction ($V_{DSI,down}$) or load increase ($V_{DSI,up}$) is balanced in a negative, loss-free storage (Equation (11)). For this, the specification applies that after a certain period or at a certain point in time, the storage level ($V_{FillLevelDSI}$) must be at zero.

$$V_{FillLevelDSI}(t+1) = V_{FillLevelDSI}(t) + V_{DSI,down}(t) - V_{DSI,up}(t) \quad (11)$$

The technical restrictions and the resulting shift potential are implemented per technology. A detailed description, as well as the basic principles of the flexibility option, can be found in [24]. In the present study, a version is used that specifies a point in time when the energy demand must have been finally covered in order to adequately capture the shift potential of intelligent charge controls.

The chosen representation makes it possible to realistically consider the flexibility from electric mobility in the electricity market model. The implemented restrictions are the potential that varies over time, which was determined from empirical data, and the specification of a vehicle that is charged regularly. The electricity market model continues to assume no costs or losses for the use of the flexibility from BEV, as it is assumed that no additional costs are incurred by the mere shifting. The use of other DSI options, e.g., shiftable loads in industry, which are associated with costs, are not considered in this study.

2.4. Scope

The newly developed approach is demonstrated in a scenario for Germany with ambitious CO_2-reduction targets for the energy sector. The chosen framework is the scenario "KS95", which was developed in the study "Klimaschutzszenario 2050" [25]. It assumes a CO_2-reduction of 95% for the year 2050 compared to 1990. This means that in 2050 only 18.6 mt of CO_2 may be emitted to cover the demand for electricity. Furthermore, a path for the penetration of electric vehicles is assumed. For 2050 in total, 21.6 million BEV are assumed. The hourly resolved charge power demand from the previous simulation is scaled to the number of cars, which results in a demand of 61 TWh. Together with a time series on conventional demand of 375 TWh, this leads to a total electricity demand of 436 TWh.

In the present study, an investment calculation in power plants and flexibility options, without existing power plants, is carried out to cover the hourly demand. This so-called greenfield calculation serves to analyze effects detached from an existing power plant park.

Possible technology options are gas combined cycle plants (*GasCC*), Gas turbines (*GT*) and renewables (PV, wind onshore, wind offshore), which can be curtailed. Furthermore, an investment in storage with different energy-to-power (*E2P*) ratios is possible (short-term storages with an *E2P* equal to 2 and mid-term storages with an *E2P* equal to 7, such as battery storage systems in different setups, and long-term storage with an *E2P* equal to 500, such as hydro pump storage). Nuclear power plants as well as hard coal and lignite power plants are not included due to political decisions of a phase out [26]. The data for the investment options and further model data are given in the Appendix B.

For the year 2050, a certain degree of expansion of the renewable technologies PV and wind on- and offshore is stipulated in the given scenario, but is calculated endogenously as part of the optimization problem. Since the profiles of these technologies affect the model results and thus the investment decision in different assumptions in sensitivity calculations, the following calculations assume a fixed investment ratio of PV, wind offshore and wind onshore to receive robust results, as also done in [22]. The scenario specifies that the ratio should be 3.3 times the invested capacity of wind onshore and 2.9 times the invested capacity of PV compared to wind offshore.

Potential restrictions for renewable energies or storage technologies are not specified. The scope for the study is limited to Germany; imports and exports from neighboring countries are not considered.

2.5. Determination of Profile Cost

In order to quantify the costs of integrating electric mobility into the electricity supply task and to show the possibilities offered by the flexibility potential, this paper also focuses on profile costs as part of the system costs.

Profile costs of renewable energies arise from a profile that does not match the demand to be covered. For example, a photovoltaic system can provide a large amount of energy, but due to the inappropriate generation profile dependent on the solar radiation, it may not meet the demand at a given time. There is a time lag between supply and demand. In the research field of energy system analysis and electricity market modeling, profile costs have been part of various studies for several years. Due to the increasing share of renewable energies in power generation, this part is becoming more relevant. The authors of [27] characterize the profile costs as part of integration costs by analyzing different cost components of renewable energies. They split profile costs in backup costs, full-load hour reduction and overproduction costs and propose an approach to quantify them as well as a graphical interpretation via a residual load duration curve (*RLDC*). Furthermore, profile costs are described as "the marginal costs of the temporal variability of variable renewable energy output" [28].

Furthermore, the work presented in [22] analyzes profile costs according to the procedure of the classical system analysis, with and without the respective technology under investigation. It examines the total system costs with all profiles and without the residual profile and thereby determines the additional costs of the residual profile. It further states that it is only possible to analyze all profiles together in a residual profile [22].

Due to the demand for electric mobility, a further profile becomes relevant for the supply task. In order to quantify the profile effect and the additional costs caused by this profile analogous to [22], calculations are performed including and excluding the demand from electric mobility, each with the given and with flat profiles for the demand and the renewables feed-in. The four results are then compared to evaluate the profiles.

Since there is no effect of *BEV-DSI* without existing demand or generation profiles, the expected reduction of total system costs with profiles also defines the difference in profile costs with and without intelligent charging. An evaluation of the flexibility is therefore not possible. Hence, the consideration of the *RLDC* is supportively used to evaluate the effect of *DSI* on profile cost qualitatively.

3. Results

In this chapter, the results of the mobility tool are presented at the beginning. The charging behavior and flexibility potential derived from the mobility curves are presented exemplarily. These serve as input for the calculations in the electricity market model. The results for the total system costs, the installed capacity and the flexibility input are determined and compared in various sensitivity calculations.

3.1. Results of the Simulation of Mobility and BEV Load Curves

Figure 3 shows the average mobility curve for a Monday determined for the period in spring. Since the mobility tool is simulating the mileage per quarter hour, the values are summed up to hourly values. The mileage is furthermore normalized by all *BEVs*, resulting in values between 0 and 6 km. It is shown that the first journeys during the course of the day take place after 4 a.m. The mobility need on the Monday is highest in the morning and evening, while on weekends, the greatest demand usually is at midday.

If the charging behavior is derived from the determined mobility behavior, the charging curve for the assumed 21.619 million *BEVs* shown in Figure 4 is obtained exemplarily for Monday and Saturday in winter.

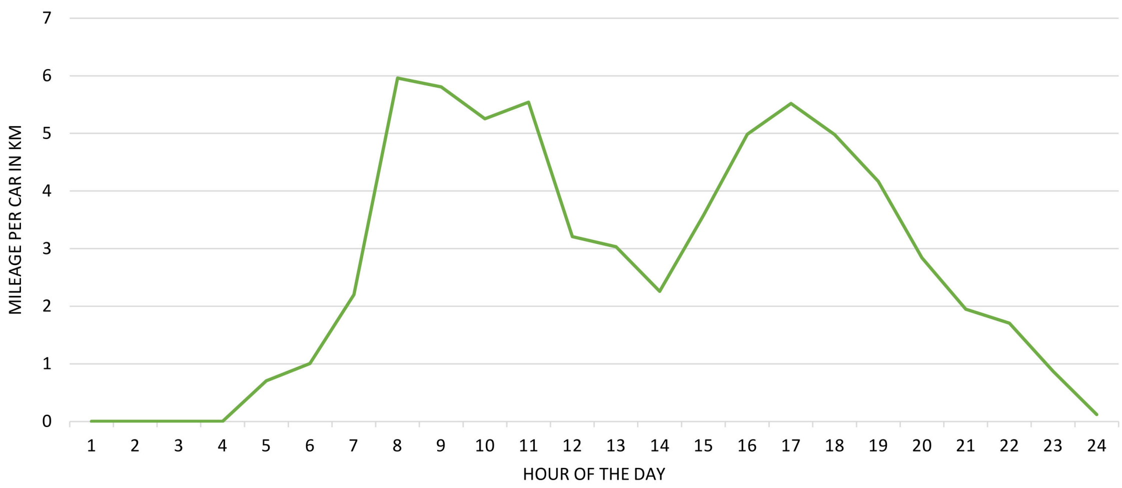

Figure 3. Mobility profile for a Monday in spring, normalized by all *BEVs*.

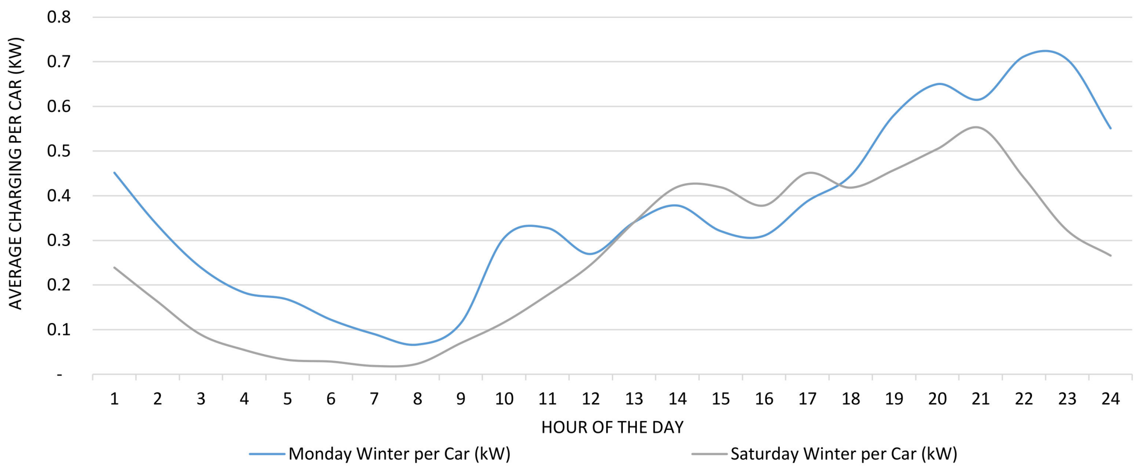

Figure 4. Load per *BEV* for a Monday (blue line) and a Saturday (grey line) in winter season.

The illustration shows that the maximum charging power occurs in the evening hours and flattens out with time until early in the morning. In the morning hours there is a low charging power demand. This can also be seen on Saturday. The charging power has a lower peak there, but is already at a relatively high level from midday until the evening. To validate the results, a qualitative and quantitative comparison with other studies, for example ([29], pp. 16–17), shows that the simulated hourly electricity demand profile from uncontrolled charging is realistic.

All vehicles are connected to the network until the beginning of their first journeys. After their return, they are reconnected for charging. The grid contact curve is derived from the driving profiles and the charging power requirements. As described in the methodology section, the load increase potential is determined from the difference between the grid contact curve and the user-controlled charging curve. The result is shown in Figure 5 as an example for a Monday in spring and in winter. The figure shows that there is a great potential for increasing load, especially in the morning hours until about 7:00 a.m. In the midday hours, the low maximum charging power and the grid contact curve ensure a low *PowerUp potential*. In the course of the day, the load reduction (or *PowerDown*) potential increases. User-controlled charging in the evening hours reduces the positive load shift potential there, whereas the load reduction potential is more available.

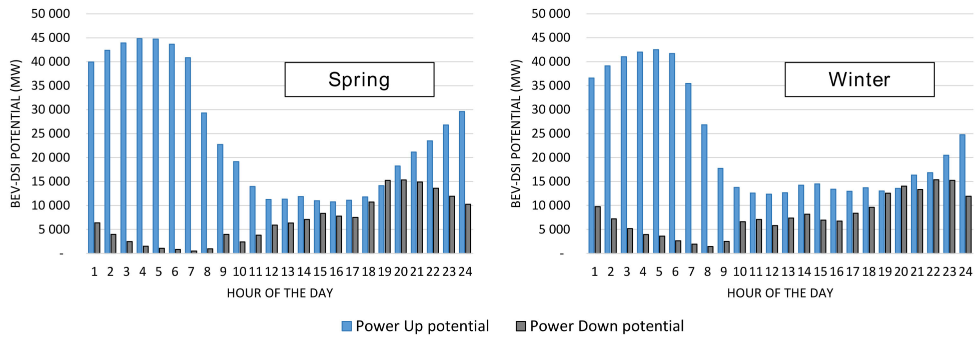

Figure 5. PowerUp (blue) and PowerDown (dark grey) flexibility potential of all *BEVs* for a typical Monday in spring and winter terms.

In the electricity market model as described in Section 2, the flexibility potential presented is subject to the additional restriction that the energy of the postponed charging process must be compensated at a fixed time every day. After analysis of the result of the mobility behavior, this point in time is set to 6 a.m., since most of the distances covered during the day are not covered until this hour (see also Figure 3).

3.2. *Results of the Energy System Modelling*

In this section, the results from the electricity market model are presented. First, the use of the newly implemented flexibility option, the shift of the charging load, is qualified. As a basis for the evaluation of the system effects, a reference result without flexibility of *BEV* is shown. In comparison, the scenario with additional flexibility from electric mobility is evaluated. Further sensitivity analyses are carried out. The effects of a stronger penetration and readiness for intelligent control of the charging process are analyzed. In addition, the changed use of flexibility and the possible benefit from a different compensation time point (*CTP*), the moment when the charging process must be completed, are determined.

3.2.1. Use of Flexibility in the Market Model

Figure 6 shows, for an exemplary period of 36 h, starting at midnight, the residual load (*ResLoad*, green area) and the resulting use of the flexibility of load shifting from *BEV* loads (*BEV PowerDown*/*Up*, in blue or light blue). Additionally, the corresponding fill level of the *DSI*-storage is shown as black dashed line on the secondary axis.

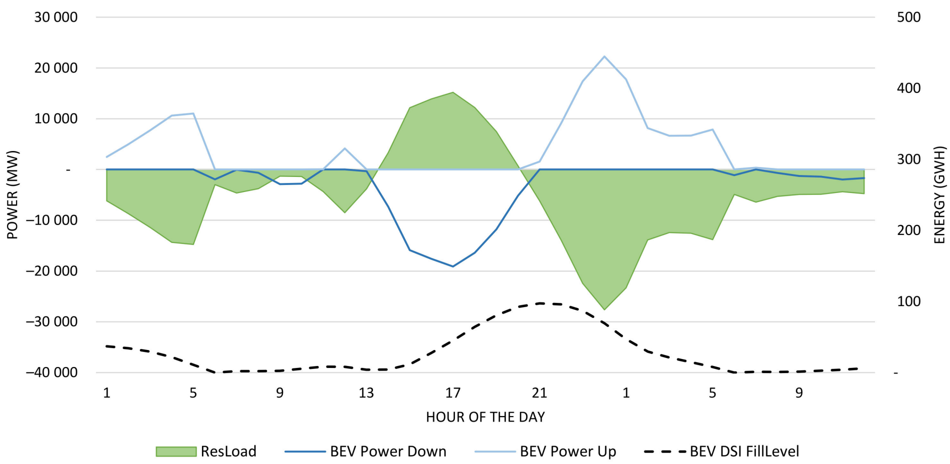

Figure 6. Use of *BEV-DSI* potential (PowerUp in light blue, PowerDown in blue) for 36 h to meet the residual load demands (ResLoad, green area). The corresponding fill level of the *DSI* storage is depicted in black dashes on the secondary axis.

On a day after 6 a.m., the load is first reduced, i.e., the flexibility storage (black dashed line, secondary axis) must be charged before the demand can be met and the charging capacity can be increased. It is shown how at times of positive residual load the demand is reduced by *BEV*-loading and at times of negative residual load the demand is increased. It can also be seen that the flexibility is also used to reduce demand during times of negative residual load in order to be able to reduce demand later with higher negative residual load. The shift is also reflected in the resulting demand after loading the *BEV* (see Figure 7).

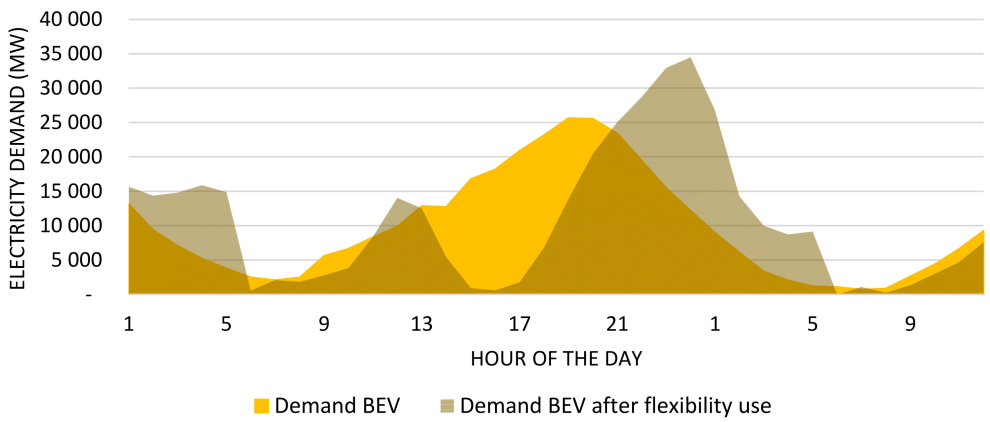

Figure 7. Electricity demand due to the *BEV*-charging process before (yellow) and after the flexibility use (brown, transparent) for an exemplary day.

The peak of the original demand by *BEV* charging (in yellow) changed from the evening hours into the night. Due to the limitation of being fully charged at 6 a.m. there is no potential to increase the load at this time, only to reduce it. Therefore, the resulting charge power (in brown, transparent) is always smaller or equal to the original charge power, so the shift is limited here and the resulting curve drops sharply.

Figure 8 shows how the load shift interacts with other flexibility options in the model. In this case we show the interaction storages with different *E2P* ratios to address short-, medium- and long term flexibility behavior. The use of load management is loss-free and without costs, which is why it is preferred to the use of storage. However, the figure clearly shows how the medium-term category 2 storage (Storage Cat 2) is used in a complementary way. The negative residual load and the resulting excess energy is stored by the storage system (Storage Cat 2 Pump, in yellow) and made available again at a time of positive residual load (Storage Cat 2 Prod, light yellow), in which, together with the reduction of *BEV* demand (*BEV PowerDown*, blue), the remaining residual load is covered. The long-term category 3 storage (Storage Cat 3 charging in red, discharging in light red), on the other hand, is mainly used for balancing over longer periods and is not used here for short-term operations.

The use of load management in comparison with the use of storage and the residual load curve shows the assumed behavior that demand is shifted from the evening hours to the night within the scope of the flexibility potential. A cost-efficient use of load shifting is possible, which is why in the following the effects on the system are worked out on the basis of the effects in the selected scenario by comparing the selected scenario with and without the possibility of using *DSI*.

3.2.2. Results of the Optimization Model on the Effects of DSI on Total System Costs and Capacity Investments

The reference calculation without the possibility of intelligent charging results in system costs of 59.1 billion €. In terms of power plant investments, this results in an installed renewable energy capacity of 220 GW and a conventional capacity (*GT* and *GasCC*) of 36 GW. Storage capacities are necessary to integrate renewable energies. These include 5 GW of seasonal storage (category 3) and 31 GW of medium-term storage (category 2), which contribute 40 TWh to load coverage.

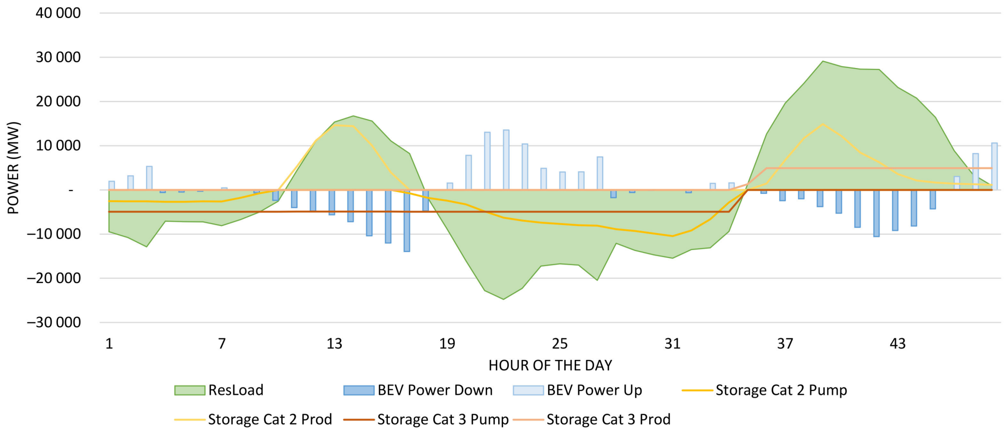

Figure 8. Interaction between the *DSI*-flexibility (blue/light blue) and the storages (Cat 2 in yellow/light yellow, Cat 3 in red/light red) to meet the given residual load (green area) for two exemplary days.

By making the charging process of all *BEVs* flexible, an additional flexibility option is available to the model, which can be used for cost-optimal demand coverage. The total system costs are thus reduced by 623 million € or 1.05% to 58.5 billion €, which is mainly due to the reduced fixed costs, as can be seen from Table 3, which compares the runs with and without the possibility for *BEV-DSI* usage.

Table 3. Comparison of the resulting costs for the scenario with and without the possibility for *BEV-DSI*-usage.

Costs and Cost Reduction	No BEV-DSI	With BEV-DSI
Total System Costs (bil. €)	59.132	58.508
Fix Cost (bil. €)	54.320	53.711
Variable Cost (bil. €)	4.511	4.797
Reduction of System Costs (bil. €)		0.623
Reduction of System Costs (%)		1.05

In terms of power plant investments (see Table 4), it is apparent that significantly less storage of category 2 (in total −3.2 GW) is being build. Slightly less renewable energies and combined-cycle power plants are built while slightly more gas turbines, which have comparatively low investment costs, are required.

Table 4. Comparison of the resulting power plant investments for the scenario with and without the possibility for *BEV-DSI*-usage.

Power Plant Invest (GW)	No *BEV-DSI*	With *BEV-DSI*	Difference
GasCC	28.0	28.0	+0.0
GasGT	8.3	8.4	+0.1
Storage Cat 2	30.8	27.6	−3.2
Storage Cat 3	5.0	5.0	−0.0
PV	88.8	88.3	−0.5
Wind Offshore	30.6	30.4	−0.2
Wind Onshore	101.0	100.5	−0.5

Table 5 shows the amount of generation from the invested capacities as well as the dispatch of flexibility options (storages and *DSI*). With *BEV-DSI*, less energy (7 TWh) is temporarily stored in the medium-term storage facilities, which leads to lower losses. In total, 13.7 TWh of the total power demand of electric vehicles, amounting to 61 TWh, are shifted. Calculating the system cost savings per shifted MWh results in 46 €/MWh. Converted to the number of *BEVs* involved, this results in a saving of 29 € per vehicle.

Table 5. Comparison of the resulting energy production and the use of flexibility options for the scenario with and without the possibility for *BEV-DSI*-usage.

Energy Production and Flexibility	No *BEV-DSI*	With *BEV-DSI*	Difference
Energy Production (TWh)			
GasCC	53.8	53.9	+0.1
GasGT	1.1	1.1	−0.0
PV	76.8	76.0	−0.8
Wind Offshore	101.6	102.4	+0.8
Wind Onshore	212.1	210.7	−1.4
Stored Energy (TWh)			
Storage Cat 2	30.5	23.5	−7.0
Storage Cat 3	20.0	19.7	−0.3
Flexibility Use (TWh)			
DSI Use	-	13.7	+13.7

3.2.3. Analysis of the Influence of a Varying Share of Participating BEV and a Different Time of Compensation at the Results of the Market Model

Since it cannot necessarily be assumed that all vehicles will participate in the *DSI* measures and this may not be necessary, this section will examine the issue in this context. In Figure 9, the course represents the system cost reduction over the share of *BEVs* participating in the flexibilization measures. It is shown that a large part (about 72%) of the achievable system cost reduction by smart charging is already achieved with a participation of 50% of the *BEVs*. At this share, this results in savings of 42 € per car. With a higher share of vehicles participating, the relative cost reduction is reduced.

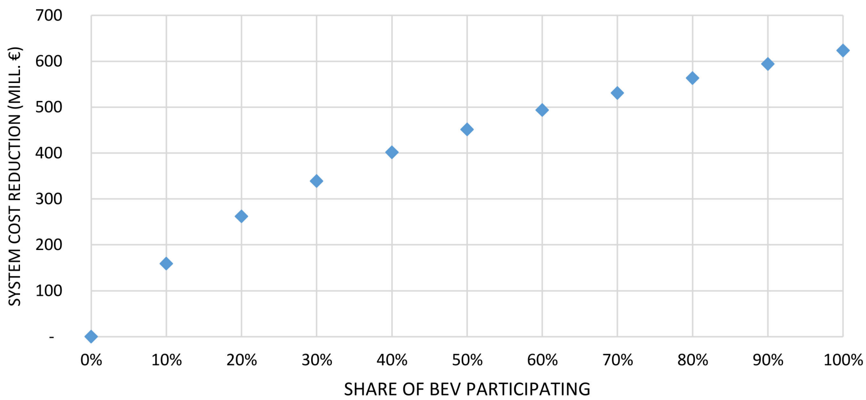

Figure 9. System cost reduction due to *BEV-DSI* in relation to the share of *BEV* participating in the measures.

The specification of a point in time when the vehicle must be fully loaded limits the flexibility of the application. As shown above, *PV* power generation at midday hours can hardly be integrated by an intelligent charge control system from *BEV*, as there is only a small total charge power requirement at this time (see Figure 5). Therefore, it is investigated what a shift of the compensation time point to other times can cause under the same assumptions. The varying effect of *BEV-DSI* by comparing the resulting total system costs with different *CTP* is shown in Figure 10. It shows, on the left side, the total system costs for scenarios without *BEV-DSI* and with *BEV-DSI*, but with changing *CTP* for four different moments during a day. On the right side, the relative cost reduction is depicted.

The figure shows that a *CTP* at 6 p.m. has the highest reduction in terms of system cost reduction, up to nearly 3 percent, while a shift of the *CTP* from midnight to 6 a.m. does not change a lot.

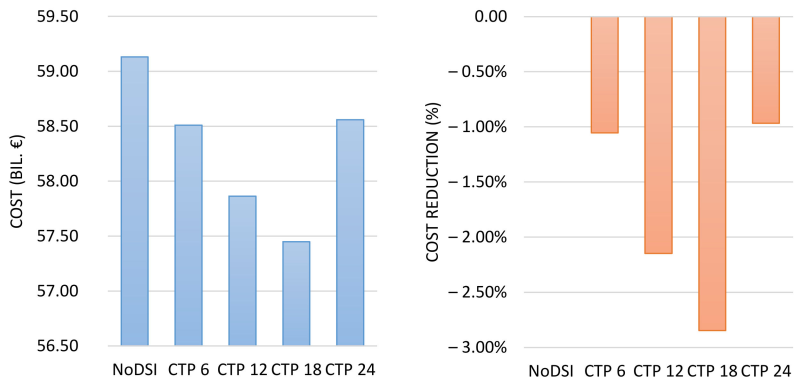

Figure 10. Total system costs (**left graph**) and relative cost reduction (**right graph**) by changing the preset compensation compared to the reference scenario without *BEV-DSI*.

3.2.4. Analysis of Profile Costs

For the analysis of profile costs, five runs are compared, with and without profiles, with and without *BEV* and one with *DSI*. Table 6 gives an overview of them.

Table 6. Overview of the model runs which are used to analyze profile costs.

Name of Model Run	*BEV* Demand	Profiles	*BEV DSI*
Flat	No	No	No
Profile	No	Yes	No
BEV-Flat	Yes	No	No
BEV-Profile	Yes	Yes	No
BEV-DSI	Yes	Yes	Yes

Figure 11 shows the difference in the demand curve for one day between the setups without profiles, with (right graph) and without *BEV* (left graph) demand. It is obvious that the profile with *BEV* increases the relative demand peak (scaled to the demand peak of the day, which is 40.6 GW in the no*BEV* and 65.0 GW in the *BEV* scenario).

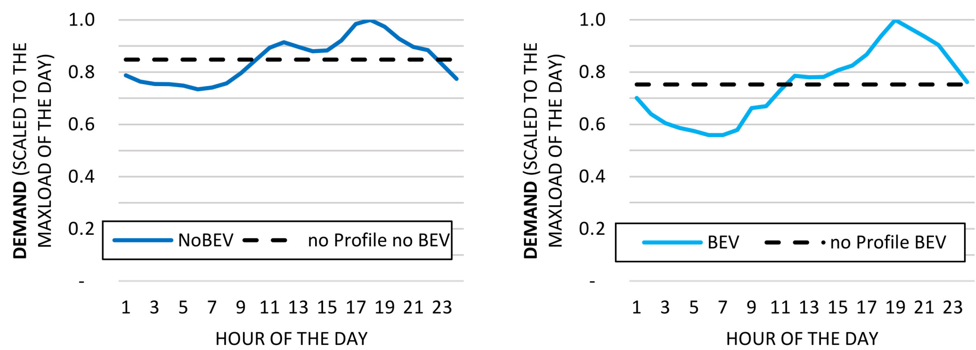

Figure 11. Exemplary depiction of the demand curves for the model runs without *BEV* (**left graph**) and with *BEV* demand (**right graph**) one time without profiles (black dashed lines) and with profiles (blue lines) for an exemplary day.

The total system costs of the model runs without profiles are significantly lower than those with profiles (see Table 7). The difference is 14.5 million € for the scenario without *BEV* and 18.7 million € for the scenario with *BEV* respectively. The share of the hereby calculated profile costs on total system costs is higher in the *BEV*-scenario higher than in the scenario without *BEV* demand (31.9% vs. 29.6%).

Table 7. Total system costs and determined profile costs for the scenarios with and without *BEV*.

Cost Component	Flat	Profile	*BEV*-Flat	*BEV*-Profile	*BEV-DSI*
Total System Costs (mill. €)	34.637	49.172	40.265	59.132	58.508
Profile Costs (mill. €)		14.535		18.867	18.243
Share of Total Costs		29.6%		31.9%	31.1%

As shown in Section 3.2.2, *DSI* of *BEV* can reduce the total system costs, needs nearly the same amount of renewable capacities but reduces medium-term storage needs. The impact on the *RLDC* is rather low because of the equal renewable production (before curtailment), which can be seen in Figure 12. On the left graph, the figure shows on the left graph the *RLDC* for only the *BEV*-Profile Scenario, because it does not differ graphically to the results of the *BEV-DSI* model run. The important parts of the graphic are marked, oriented on the representation of [27], Here "A" marks the back-up demand, defined by the maximum residual load, "B" addresses the full load hours of conventional generation and storage capacities while "C" represents overproduction. The back-up need for the run with *DSI* is slightly higher (17 MW). For the further evaluation of the results, on the right side of Figure 12, the difference of the absolute *RLDC* values between the runs without and with *BEV-DSI* are shown. The figure shows that the full load hours (area B) are higher in the run with the *DSI*-option, and therefore the specific costs of the energy production are reduced. Overproduction is higher without *DSI* (area C), which accounts for 1.75 TWh in total. The sum of these effects leads to higher total system costs and therefore to the higher profile costs in the scenario without *BEV-DSI*.

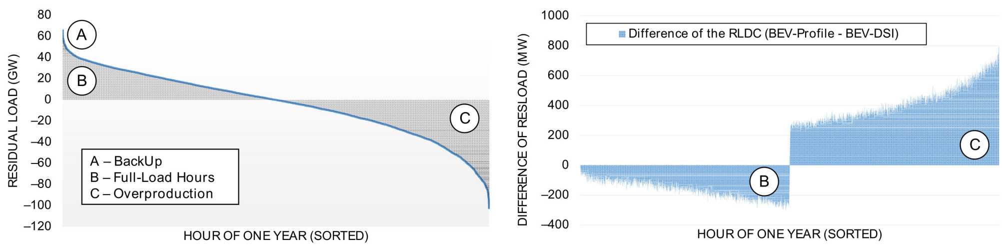

Figure 12. Residual load duration curve, congruent for the *BEV* scenarios (left graph), with the areas for the back-up need (**A**); full-load-hours (**B**) and overproduction (**C**). The right graph shows the resulting differences between the scenario without and with *BEV-DSI* concerning the FLH-reduction (**B**) and the overproduction (**C**). Concept of the figure based on [27].

4. Discussion

The approach displayed in this paper shows a methodology to determine the flexibility potential by load shifting during the charging process of *BEV* and to consider it in an electricity market model. Due to the chosen method of the Markov-Chain Monte Carlo simulation for the determination of the mobility and charging power demand, as well as the chosen definition of flexibility, it is possible to consider the restrictions of the driving behavior of individuals and at the same time to determine the system-optimal use of the flexibility potential.

The derived mobility curves lead to an hourly demand for electricity through the charging process of the electric vehicles. Here, high simultaneities are evident, resulting in high load peaks in the late evening and thus, with a high penetration of electric vehicles, significantly changing the profile of the electricity generation required to meet demand. This also leads to an increased demand for flexibility options.

The batteries available in the electric vehicles can, if used correctly, be systemically useful and represent a possible flexibility. As shown in this paper, this flexibility is considerably confined by restrictions from user behavior and availability is highly time-dependent.

In order to determine the benefit of the flexibility potential integrated with the time-varying generation from renewable energies and the conventional electricity demand, this paper implements flexibility as a *DSI* option in an electricity market model. In the analyses shown it becomes clear that the implementation of an intelligent charge control has a cost-reducing effect on the design of a decarbonized energy system with a high share of renewable energies.

The majority of the energy supply in the scenarios is provided by renewable energies, which, however, require a high degree of flexibility in order to compensate for supply-dependent fluctuations on the one hand and to enable cost-efficient integration on the other. By implementing *BEV* flexibility storage, requirements are reduced while the investments in renewables are not reduced. Since renewables are often questioned due to the high capacities and the associated space requirements, intelligent charge controls cannot make a major contribution in this area, but *BEV* can nevertheless reduce the (partly self-induced) system costs.

The analyses also show that it is not necessary to upgrade all vehicles or charging stations for flexibility provision. With the participation of 50% of *BEVs*, enormous positive effects are achieved, which increase at a slower rate as the share of participating *BEVs* increases. Since no costs (neither for development nor for deployment) were assumed in the analysis carried out, an optimal ratio must be evaluated in comparison with the additional expenditures in further investigations.

Quantifying the cost reductions per participating vehicle or energy used shows what possible financial incentives could be created. A player in the electricity market could use the flexibility to make profits in the electricity market. For this, the vehicle owner must be offered a financial (or even qualitative) incentive and the costs for the (additional) intelligent infrastructure must also be offset.

Considering the change in the specified loading time and the additional cost reductions that can be achieved as a result, it becomes clear that a point of completed charging in the evening at 6 p.m. is particularly advantageous. This suggests that (intelligent) charging stations should be set up at the workplace to integrate these vehicles. The implementation could either be carried out by a service provider or the company itself. The actual proportion of vehicles that can be used for this purpose is not explicitly stated here and determines the actual flexibility available.

From a systemic point of view, the advantage of a later point in time can be explained by the integration of *PV* power. The charging power demand from the morning hours can be shifted to the afternoon and thus use the peak generation from the *PV* systems. In addition, the load peaks that occur in the evening can be flattened out by classic electricity demand and electric mobility.

Profiles of electric mobility charging contribute significantly to the total system costs due to the necessary flexibility options and the different share of renewable power generation that can be integrated. They should therefore be explicitly identified when quantifying the costs. A possible method offers the evaluation of the *RLDC*, which gives insights on the temporal matching of electricity demand and renewable generation (and overproduction). Profile costs do not only arise from the expansion of renewable energies, but also from new consumers such as *BEVs*. The decisive factor is the combination of profiles and the availability of flexibility options. At this point, the analysis of the electricity market may neglect the grid costs that arise from regional differences in the profiles.

5. Conclusions

The study shows a new approach to derive the flexibility potential of electric vehicles available for the electricity market on the basis of simulated charging curves taking into account the real driving behavior of individual vehicles. The charging demand and the identified flexibility potential are integrated into an electricity market model to quantify the effects on total system costs as well as the necessary flexibility demand in a scenario with ambitious climate targets. It is shown that the high demand for electricity from electric vehicles leads to a considerable increase in the need for renewable energy capacities, which in turn increases system costs. The flexibility of intelligent charging stations can support the integration of renewable power generation and reduce the necessary storage requirements. The assumption for the time when the BEV has to be completely charged influences the cost reduction potential, with the best use of flexible charging during the afternoon. Furthermore, it is shown that the profile of the electricity demand in combination with the generation profile of the weather-dependent renewables feed-in, and additionally the availability of flexibility options, has a great influence on the design of the energy supply and thus on the total system costs.

In the modelling process some limitations have been identified, and a higher level of detail in these areas may provide further insights. Since the actual charging behavior cannot yet be foreseen in the future, further charging patterns, such as charging only at the weekend or only when the battery level is below 50%, could be investigated here. In addition, the assumptions that all users have the same behavior and that the charging power is maximum 3.7 kW could be revisited. Some vehicles are going to be charged at work and, as there is a strong dependency on the charging time, it might therefore be useful to add more than one user group to increase the level of detail. In the coming years, further experience and data from users of electric vehicles will provide more insights.

In this study, we do not analyze effects on the electricity grid, even though there will be issues concerning peak loads (especially in the distribution network) induced by technologies with significant profiles such as BEV or PV and this will therefore will make flexibility on a regional level necessary. Aggregators can combine the flexibility of intelligent charging of $BEVs$ with other options with complementary limitations such as heat pumps or other technologies to offer it on relevant markets.

To what extent users are willing to leave the control of their charging process to third parties is also a question of acceptance, which, like legal issues, still needs to be clarified. The financial incentive for private households (or aggregators) to sell the charging flexibility on electricity markets would therefore have to be correspondingly high.

The modelling of mobility behavior, BEV-charging curves and flexibility potential shown in this paper provides a basis for discussion to evaluate the impact of a rising penetration of electric vehicles with an additional energy demand and changes in the electricity system and its costs.

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Appendix A. Data for the Mobility Tool

Table A1. Data for the simulation of the mobility and charging load, data source: [30–32].

Parameter	Parameter Value	Comment
Vehicle-to-Wheel-consumption (kWh/100 km)	18.0	Quantity weighted consumption
Charging Power (kW)	3.7	
Charging Losses (%)	13.4	
Grid-to-Wheel consumption (kWh/100 km)	20.8	
Range (km)	345	Prognosis for 2020, assumption, that 20% less range than with NEDC
Battery Capacity (kWh)	71.8	

Appendix B. Data for the Electricity Market Model

Table A2. Data for power plant investment options, data source [22,25].

Power Plant	Efficiency (%)	Lifetime	Invest Cost (€/kW)	Annual OaM Costs (€/kW)	VarOaM Cost (€/MWh)	Full Load Hours
GasCC	61	30	780	22	1.5	
GasGT	41	30	400	15	1.5	
Storage Cat1 E2P 2	81	20	714	10	2.5	
Storage Cat2 E2P 7	81	20	1059	10	2.5	
Storage Cat3 E2P 500	81	20	9219	10	2.5	
PV		25	1150	34	0	949
Wind Offshore		20	2850	120	0	4000
Wind Onshore		20	1400	50		2598

Assumed Interest Rate: 7.5%, Primary energy prices are based on the KS 95 [25]. Synthetic profiles for renewables and demand are taken from [33], based on the year 2018.

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