energies

Article

Analyzing the Charging Flexibility Potential of Different Electric Vehicle Fleets Using Real-World Charging Data

Vincent Barthel [1], Jonas Schlund [1], Philipp Landes [2], Veronika Brandmeier [2] and Marco Pruckner [1,*]

[1] Energy Informatics, Computer Science 7, Friedrich-Alexander-University Erlangen-Nürnberg, 91058 Erlangen, Germany; vincent.barthel@fau.de (V.B.); jonas.schlund@fau.de (J.S.)
[2] The Mobility House, 81669 Munich, Germany; philipp.landes@mobilityhouse.com (P.L.); veronika.brandmeier@mobilityhouse.com (V.B.)
* Correspondence: marco.pruckner@fau.de; Tel.: +49-9131-85-27697

Abstract: A successful transformation of the energy and transportation sector is one of the main targets for our society today. Battery electric vehicles can play a key role in future renewable-based energy supply systems because of their ability to store electrical power. Additionally, they provide significant charging flexibility due to the long parking durations. In this paper, we provide insights into the temporal and power-specific flexibility behavior of three different vehicle fleets. These fleets are pool vehicles of office employees, a public authority, and a logistics company. Several parameters, such as the average charging power per charging event or the average plug-in duration per charging event, are discussed. Additionally, we investigate different charging rates and their impact on the temporal flexibility of the charging events. The data analysis shows that the logistics site has the most homogeneous charging profile as well as high charging flexibility, in contrast to the office and public agency site. The results are of significant importance for future applications in the field of smart charging and ancillary services provision.

Keywords: electric vehicles; vehicle grid integration; charging flexibility; data analysis; optimization; smart charging

Citation: Barthel, V.; Schlund, J.; Landes, P.; Brandmeier, V.; Pruckner, M. Analyzing the Charging Flexibility Potential of Different Electric Vehicle Fleets Using Real-World Charging Data. *Energies* **2021**, *14*, 4961. https://doi.org/10.3390/en14164961

Academic Editor: Ahmed A. S. Mohamed

Received: 27 June 2021
Accepted: 5 August 2021
Published: 13 August 2021

1. Introduction

The sustainable transition of our energy and transportation systems is one of the central challenges for our society today. Globally, the two sectors of energy and transport are responsible for more than 50 % of annual greenhouse gas emissions [1]. While renewable energy sources are increasingly replacing fossil-fueled power plants in the energy sector, plug-in electric vehicles (EVs) play a key role in the transportation sector to drastically reduce local tailpipe emissions. The expansion of renewable energy sources (RES) leads to higher fluctuations and a high dependency on the time of day and weather conditions. For instance, the curtailed energy amounted to more than 6 TWh in Germany in 2019 [2]. Therefore, there is a strong need for flexibility to better integrate the electricity generated by RES. On the other hand, the introduction of more and more plug-in EVs offer great flexibility potential. This flexibility potential can be utilized by smart-charging technologies and energy management systems, such as ChargePilot by The Mobility House [3]. ChargePilot intelligently manages EV charging, according to local requirements (e.g., grid connection) and external signals (e.g., grid congestion and energy market prices). It converts EV batteries into storage assets that can stabilize the grid and buffer renewable energy. The system is the basis for the future participation of EVs in the energy markets, which offers new possibilities in terms of value-generating services and flexibility portfolios.

To better understand the flexibility potential of different vehicle fleets, it is important to analyze their plug-in and charging behavior. For instance, the plug-in behavior of an EV fleet of a logistics company can differ massively from that of a public authority. Therefore, we contribute in this paper a comprehensive data analysis of real-world charging data from three different sites—an urban office, a logistics company and a public authority. Each site has at least eight AC charging points with a charging rate between 11 and 22 kW and more than ten vehicles. In total, we analyze more than 1000 charging events and provide comprehensive insights into the plug-in behavior of these EV fleets as well as the temporal and power-specific flexibility of the charging events. Additionally, we visualize the charging flexibility by using FlexBars [4]. The results are of significant importance for several stakeholders and smart-charging providers when it comes to the evaluation of the economic potential of controlled charging strategies and the provision of system services under real-world conditions.

The remainder of this paper is structured as follows: In Section 2, we provide an overview of related work in the field of charging flexibility and data analysis of EV charging data. More information about the real-world input data and the data preparation steps is given Section 3. Section 4 provides insights into the plug-in behavior on different sites and the resulting flexibility potentials. Finally, Section 5 concludes the paper with a short summary and an outlook on future work.

2. Literature Review

2.1. Electric Vehicle Charging Data Analysis

The analysis of real-world EV charging data is becoming increasingly important to gain a better understanding of user behavior. For instance, in order to develop accurate prediction models for the plug-in duration or the amount of energy needed for a trip, a comprehensive understanding of user behavior is essential. There are some recently published studies that focus intensively on the charging behavior of EVs in the area of workplace or residential charging.

Gerritsma et al. [5] analyzed the simultaneity of charging events in a residential area in the Netherlands by utilizing the real-world data of 21 charging stations. The time-dependent flexibility of the resulting EV demand is used to simulate the charging behavior of future EV fleets. Interesting insights of the charging behavior of 20 EVs on the Portuguese island of Porto Santo are shown in Strobel et al. [6]. The given data analysis points out that drivers prefer home charging rather than away charging and that flexible charging events occur mostly overnight. Because the users of the EV fleet changed over the project period, there are no general user group-specific statements about the charging flexibility possible. ACN-Data [7] provides a comprehensive dataset of charging events at JPL and CalTech campuses, which is updated in real-time. For each charging event, the plug-in time, the plug-out time and the amount of energy charged is logged. This dataset provides the basis for many other publications [8,9] in this area, for instance, in the work of Khan et al. [8] to predict user behavior, or in the paper of Venegas et al. [9] to analyze the grid integration of renewable energies in more detail. The ElaadNL data platform contains aggregated data from public, private and workplace charging stations distributed over the entire Netherlands [10–12]. The dataset shows important key figures, such as the time of the charging event or the idle time [10]. In Lahariya et al. [13], the authors develop a synthetic data generator for EV-charging sessions based on the ElaadNL dataset. For the synthetic data generator, the authors assume that the EV inter-arrival time follows an exponential distribution. The departure time is represented by a conditional probability density function. The synthetic data generator can be shared without violating the confidentiality constraints. Xydas et al. [14] use real-world charging data from the U.K. to develop a data-mining model for the EV charging demand. The model is used to analyze the characteristics of EV charging demand in a geographical area. An EV charging dataset that is more focused on the user behavior in residential areas is provided by Sorensen et al. [15,16]. The authors analyze the charging habits and electricity load profiles of EV charging in apartment buildings in Norway. Results show that there is a big charging flexibility in residential areas as long as private parking spaces are utilized with EV charge points. Rauma et al. [17] analyze over 80,000 real-world charging sessions from various commercial charging sites. There findings indicate that residential and office charging sites offer a great potential for load reduction.

2.2. Charging Flexibility

As mentioned above, the analysis of real-world EV charging data provides useful insights into the charging behavior of individual users or bigger EV fleets. This knowledge can be used to describe the charging flexibility in greater detail and to better understand possible application areas, such as load balancing or auxiliary service provision.

For the description of flexibility by consumers in general, i.e., not specifically for an application, the model of FlexOffers [18,19] is often used. FlexOffers were introduced to specify supply-side and demand-side flexibility and create an approach to use as much of the available flexibility as possible in real-time. The results show the better integration of RES and peak demand reduction [20]. Pederson et al. [21] provide a good overview of the principle of FlexOffer. Basically, FlexOffers are divided into time and energy flexibility, and the application takes place as follows: (1) collection of the data of the flexible loads; (2) preparation of the data (elimination of "outliers", and filling of data gaps); (3) flexibility forecasting using a model; (4) generation of the FlexOffers—time and energy flexibility; (5) aggregation/disaggregation of the FlexOffers (for easier marketing); (6) trading the flexibility in the market and creating a schedule; and (7) the schedule is given back to the flexible loads for compliance. The objective of the FlexOffer method is to achieve easy management, control and market integration of flexibility. The providers of the flexibility can be versatile, ranging from power plant operators to large consumers to prosumers. The disadvantages of the FlexOffer model are, first, the loss of flexibility along the process chain and, second, the lack of real-time use of flexibility. In addition, other grid parameters, such as voltage and frequency are not considered in the model. Schlund et al. [4] further develop the FlexOffer system by providing a general model for determining guaranteed currently available flexibility through flexible distributed loads. The model takes into account energy, power and time. In addition, the authors present the possibility of bidirectional power flexibility in the presence of unidirectional charging EVs. The model is evaluated by means of simulation of EVs in which a realistic mobility behavior is emulated, and, thus, no real data of EVs are used. In principle, the *FlexAbility* model introduced here allows a description of flexibility through distributed loads while respecting important energy constraints. Contributing to the auxiliary services, such as the frequency containment reserve, is feasible with this model. The possibility of visualizing the charging flexibility through FlexBars is taken up in this work and used to illustrate the temporal and power dependence of charging operations for different vehicle fleets. Another approach for the description of charging flexibility is provided by Li et al. [22].

Grid-serving charging strategies under the consideration of mobility needs are investigated by Sundstrom et al. [23]. The authors demonstrate the flexibility potential of EV fleets by studying load-shifting mechanisms. Pertl et al. [24] conclude that smart charging can save necessary grid expansion costs and better integrate RES into the grid. Therefore, they implement a so-called time-variant energy storage model consisting of many EV batteries. In this way, the forecast errors can be better absorbed. In the absence of the time dependence of power and energy, the implementation of system services is also possible in this model. Sperstad et al. [25] examine the impact of flexibility on energy system security. They identify the possible rebound effect from incentive-based load shifts as a negative impact. The growing dependence of system stability on the flexibility built on forecasts and models as well as the increasing risk of sabotage and cyber attacks, due to the necessary use of Information and Communication Technology, are additional negative factors. The latter is also discussed in Amini et al. [26]. They argue that, with the use of flexibility, the utility network can be used more efficiently. On the other hand, however, also the utilization increases, which increases the susceptibility of the network to faults. Spitzer et al. [27] study the impact of uncontrolled charging on a residential low-voltage network. The authors come to the conclusion that uncontrolled charging leads to peak loads in the evening hours that cause voltage fluctuations in the grid. To overcome these problems and to better utilize the charging flexibility, smart charging strategies based on dynamic electricity tariffs are implemented, using mixed-integer linear programming. The results show that cost savings of up to 30% are possible, showing the great flexibility potential of overnight charging in residential areas. The impact of flexible charging of EVs is also discussed by Bons et al. [28]. In their work, the authors present the results of a demonstration project called Flexpower. They indicate that the EV contribution to the grid peak load can be reduced by 1.2 kW per charging station, whereas the impact on the user is quite low.

The objective of this work is to provide a general method for analyzing the market and flexibility potential of an electric-powered vehicle fleet based on real-world data. The temporal and power-specific flexibility of charging events from different areas of electric mobility usage is analyzed and quantified. For visualization and simplified estimation of the flexibility potential, FlexBars according to Schlund et al. [4] are used.

3. Input Data

The data used as input for our study were extracted from the charging and energy management system, ChargePilot, developed by The Mobility House. Inter alia, it covers the entire EV fleet of three different sites discussed in this paper. In this section, we first describe the data preparation steps in general. Secondly, we discuss the input data in more detail.

3.1. Data Preparation

In this work, we use real charging data from three different vehicle fleets as input data. Therefore, the raw dataset is only available in an aggregated way, representing the grid connection point of each site. In order to generate insights into the charging flexibility of individual charging events on each charging station of a specific site, we have to perform several data preparation steps.

In the following, a charging event refers to the period of time during which a vehicle is physically connected to a charging point—consequently, the time span between plug_in and plug_out time. The term charging process is used to describe the actual duration of the energy consumption, i.e., the time during which the battery is charged. Hence, idle times where the vehicle is connected to the charging point but no electrical energy is drawn are only included in the charging event.

Figure 1 shows the toolchain of the data preparation process. The data preparation process can be divided into four steps: disaggregation, discretization, addition and aggregation. Each step is described in more detail in the following.

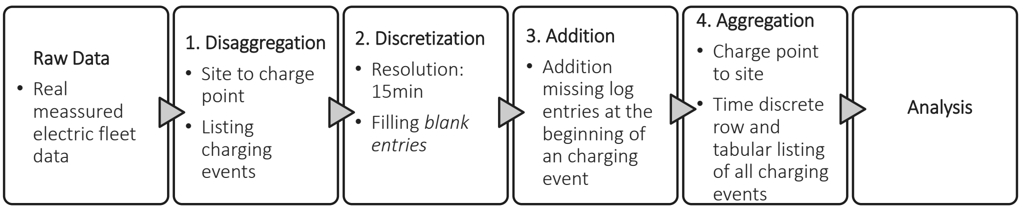

Figure 1. Toolchain: from raw data to flexibility analysis.

3.1.1. Disaggregation

Generally, each site has more than one charging point, meaning that simultaneous charging events at different charging points overlap in the raw dataset. The disaggregation of individual charging points has the advantage that the data cleaning process can be performed more accurately, and the boundary conditions of charging events can be identified more precisely. This is very helpful to quantify the flexibility potential of individual charging events.

Each individual charging event can be described by specific parameters given in Table 1. Some of the parameters can be extracted directly from the raw data, e.g., the plug-in time $T_{k,\text{plug\_in}}$ for the charging event k. Other parameters can be derived by simple calculations or assumptions. For instance, the plug_out time of a charging event is not recorded in the raw data. Therefore, we assume that the time stamp of the last available log-entry defines the plug_out time of the related charging event. Please note, that each charging event is represented by a number of log-entries in a resolution of 20 s, including several measurements, such as the time of measurement or the offered and demanded current per phase. Calculated parameters are marked with * in Table 1.

Table 1. Parameters of individual charging events.

Parameter	Meaning	Format/Unit
h	Index; indicates the h-th charging event of the charging point	-
k	Event-ID of the charging event; $k \in \Omega$, where Ω describes the set of charging events	-
$T_{k,\text{plug\_in}}$	plug_in time of charging event k	*HH:MM:SS dd.mm.YYYY*
$T^*_{k,\text{plug\_out}}$	plug_out time of charging event k	*HH:MM:SS dd.mm.YYYY*
t^*_k	Duration of the charging event k	*HH:MM:SS*
$t^*_{k,\text{charging}}$	Duration of the charging process of the charging event k	*HH:MM:SS*
$P^*_{k,\text{max}}$	Maximum charging rate of the charging event k	W
$P^*_{k,\text{mean}}$	Mean charge power of the charging event	W
$P^*_{k,\text{charging,mean}}$	Mean charge power of the charging process	W
E^*_k	Charged energy of the charging event k	W h

For the following data preparation steps, we only consider charging events that fulfill the following three requirements:

- Duration must be greater than or equal to five minutes ($t^*_k \geq 5$ min.).
- Charging rate must be greater than zero Watts ($P^*_{k,\text{max}} > 0\,\text{W}$).
- Charged energy must be greater than or equal to 100 W h.

Please note that we choose a minimum duration of five minutes to exclude charging events with communication errors between charging stations and the backend.

3.1.2. Discretization

For the flexibility analysis of the individual charging points, we discretize the data into a resolution of fifteen minutes. This corresponds to the smallest possible temporal product size on the German spot market.

The discretized data set ensures that we have the same number of log entries for each charging point. However, due to the discretization, we may obtain so-called blank entries because data are only measured and transmitted when an EV is plugged in. These can occur within a single charging event or between two charging events at the same charging point. In order to obtain a complete time series, we fill blank entries by interpolating between adjacent log entries.

3.1.3. Addition

In order to guarantee a continuous time series, we add missing log-entries. In the case of the flexibility analysis of charging events, we do not consider the missing entries.

3.1.4. Aggregation

In order to conduct a detailed site-wide analysis of charging flexibility, we finally aggregate the prepared and cleaned data from the individual charging points. A tabular listing of all charging events of a site can be obtained by linking the corresponding charging events of the individual charging points and sorting them by the plug_in time. Therefore, we introduce a charging point ID CP_n.

Subsequently, we create discrete time series for each parameter (e.g., E_k^*), which represent the sum of the related parameters of the individual charging points for each time step. For instance, Equation (1) shows the total charged energy for each discrete time step t.

$$E(t) = \sum_{k=1}^{\tilde{\Omega}} \sum_{n=1}^{N} E_k(t, n), \tag{1}$$

where N represents the number of charging points at a site and $\tilde{\Omega}$ the number of charging events. Please note that Equation (1) can also be formulated for other parameters shown in Table 1.

3.2. Data Set and Characteristics

This section describes the analyzed data set in more detail and discusses the data selection process as well as certain characteristics.

3.2.1. Data Set

We analyze the following three EV fleets from different sectors and, thus, with different charging behavior:

(a) Office site: The fleet consists of fifteen battery electric vehicless (BEVs), including five company pool vehicles and ten private-owned vehicles of employees. The office site is located in an urban region. An urban depot is where mainly company and employee vehicles are charged. Eight charging points are available.
(b) Logistics site: The EV fleet consists of twelve delivery vans (Mercedes e-Vito). Twelve charging points are available.
(c) Agency site: The vehicle depot of the public agency solely consists of twelve company vehicles of different types. Twelve charging points are available.

The data basis of our analysis is given in Table 2. Whereas the data for the office site are given for more than one year, the time period for the logistics site and agency site amounts to two months. Hence, the total charged energy and the number of charging events differ significantly. Table 2 also provides an overview of some key performance indicators, such as the average charging power per charging event or the average plug-in duration per charging event. These parameters allow a comparison between different sites.

Table 2. Data basis of the analysis.

	Office Site	**Logistics Site**	**Agency Site**
Time period	09/2019–08/2020	01–02/2020	01–02/2020
Number of charging points	8	12	12
Number of EVs	15	12	12
Total charged energy [kW h]	8179.22	5563.05	3151.23
Number charging events	509	268	374
Average charged energy per event [kW h]	16.47	20.81	8.61
Average charging power per event [kW]	7.89	10.28	9.47
Average plug_in duration per event	09:29:00	22:02:24	14:30:09
Average charging process duration per event	02:30:04	03:23:12	01:20:12

First, we note that the average charged energy per charging event at the logistics site is the highest. This fact results from the use of the fleet vehicles. Electric delivery vans have high mobility needs during workday hours because of daily parcel delivery. Therefore, the mobility requirements in terms of distance traveled is higher than those for employee and company pool vehicles. On the other hand, however, delivery vans have a very high average plug-in duration of more than 22 h per event. This is due to the fact that vehicles at the logistics site are also connected to the charging point over weekends. The average plug-in duration at the office site is mainly limited by usual working times. In contrast, the public authority site solely has service vehicles that can be connected to the charging station overnight, which leads to a higher average plug-in duration.

3.2.2. Data Selection and Characteristics

For a realistic representation of the charging flexibility of a site, we only use coherent charging events, meaning that we do not use charging events with missing log entries.

Since individual charging events of the sites deviate strongly from the average, we additionally filter the data with regard to their plug-in duration. For this purpose, we only consider charging events with a plug-in duration within an interval of 5 % to 95 % around the plug-in duration mean value. This eliminates charging events with a particularly short or long plug-in duration. For instance, a short plug-in duration results from a double-started charging process due to changing the charging point, whereas a long plug-in duration does not reflect the general plug-in behavior. This procedure contributes to a more robust database for the analysis. Removing charging events with missing log entries and filtering the data by plug-in duration reduces the number of charging events analyzed for the sites as follows: office site—509 $\rightarrow$ 400; logistics site—268 $\rightarrow$ 226; agency site—374 $\rightarrow$ 273.

By filtering the data, it is also possible to investigate the homogeneity of the user group of the respective site. The lower the number of charging events filtered out, the more homogeneous the user behavior and the better an average charging event represents ordinary charging events. The logistics site represents the greatest homogeneity in its charging behavior. The plug-in duration of the charging events at the office and agency sites shows a wider spread, which leads to a more inhomogeneous charging behavior.

In addition to homogeneity, the simultaneity of the charging processes plays a decisive role. High simultaneity with simultaneous uncontrolled charging leads to characteristic load peaks. Figure 2 shows the probability of simultaneously active charging points.

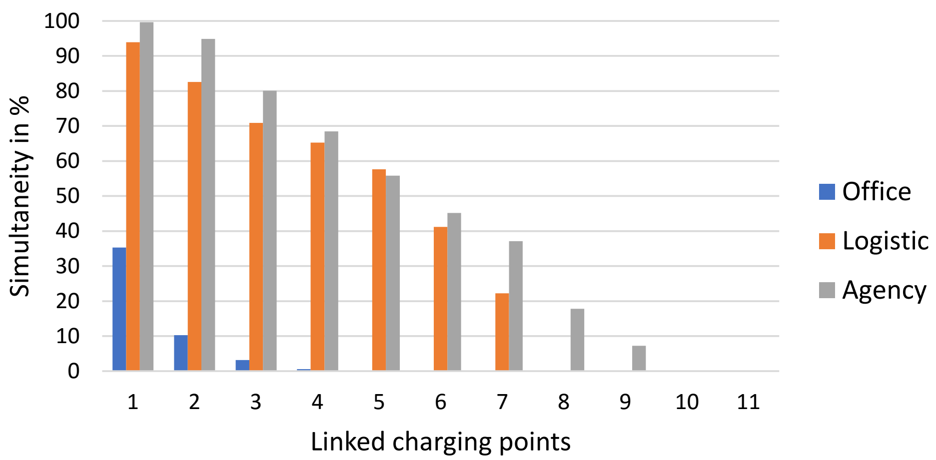

Figure 2. Probability of simultaneously active charging points of the analyzed sites.

The plot confirms the previously obtained findings that the simultaneity in the office site is lower than in the sites dominated by company vehicles, due to high heterogeneity.

For the analysis of characteristic load peaks, a weekly profile is created for each site, which represents the average power consumption caused by the charging processes. The resulting profiles of the sites are shown in Figures 3–5.

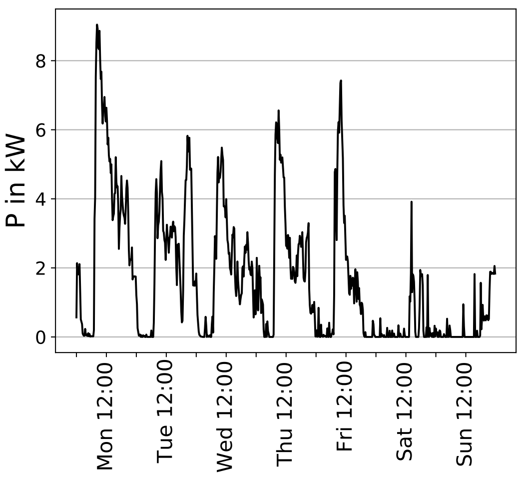

Figure 3. Weekly charging profile for the office site.

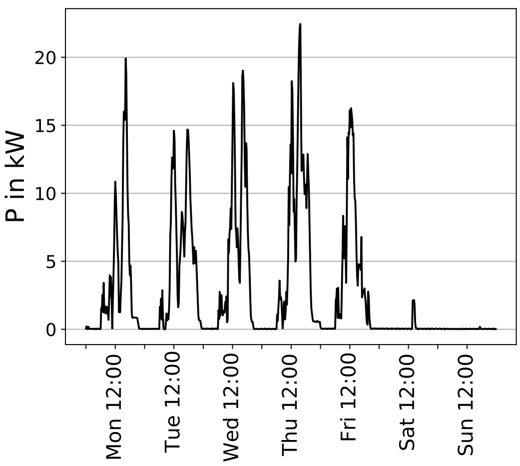

Figure 4. Weekly charging profile for the agency site.

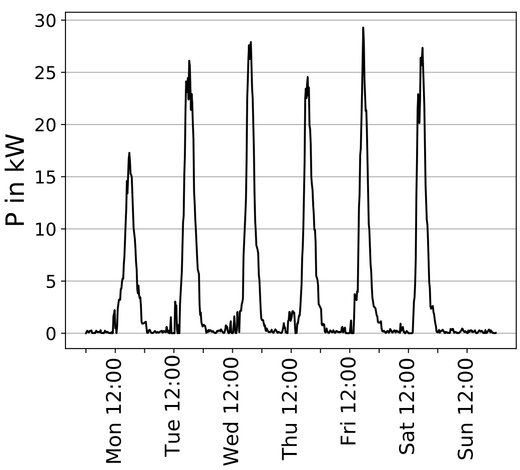

Figure 5. Weekly charging profile for the logistics site.

From Figure 5, we can see that the power profile of the logistics site is the most characteristic one. The curves show that homogeneity in combination with high simultaneity and uncontrolled charging leads to a very characteristic charging profile with significant load peaks. Decreasing homogeneity and a lower number of simultaneously active charging points leads to less distinctive curves, which becomes clear from the plots of the agency, but especially from the office site, depicted in Figure 3. The profiles of all sites indicate the usage behavior of the respective user group. The load peaks of the office site are mainly located in the weekday mornings, and thus, indicate the charging of private vehicles of the employees during working hours. At the agency site, but especially at the logistics site, the load peaks in the late afternoon hours indicate charging after work and confirm the use of company vehicles.

4. Analysis of the Charging Flexibility

In general, the flexibility of EV charging can be divided into three dimensions: time flexibility, power-specific flexibility, and energy flexibility [4]. In the following, we discuss the time and power-specific flexibility in more detail.

In the analysis of charging flexibility used in this work, the measured boundary conditions of the individual charging events are not changed. In particular, these parameters include the plug-in and plug-out time, the amount of charged energy and the maximum charging rate, which is defined as the maximum possible charging rate of the respective charging event.

In the following, we discuss the idle time and time flexibility for the investigated sites. Additionally, we also discuss FlexBars, which is a visualization method for charging flexibility defined by Schlund et al. [4].

4.1. Idle Time

The idle time is defined as the time during which a vehicle is plugged in to the charging station but no energy is being charged. Thus, it indicates the time flexibility potential of the charging processes and is calculated from the difference between the charging duration (t_k^*) and plug-in duration ($t_{k,\text{charging}}^*$):

$$t_{k,\text{idle}} = t_k^* - t_{k,\text{charging}}^* \quad k \in \Omega. \tag{2}$$

A high idle time allows to shift charging processes in time in order to avoid overloading the grid. In addition, the idle-time reflects the ability to shift charging to time periods with lower electricity prices. Thus, it is directly related to the smart sourcing potential without impairing the mobility requirement. This flexibility can be used economically by the end user, among other things, by using § 14a EnWG [29] or smart charging. This feature is already included in grid-optimized charging—an add-on module of the ChargePoint offered by The Mobility House.

For a simplified analysis of the impact of a charging event on mobility demand, we determine for each site the idle time and the probability that it exceeds two hours. Please note that if the idle time exceeds the maximum interruption time of two hours, the EV user does not experience any disadvantages in the mobility demand when using § 14a EnWG. This is consistent with most office buildings and multi-family housing in urban environments.

Figures 6–8 show boxplots of the idle times from all charging events for the office, agency and logistics sites. It can be seen that both the office site as well as the agency site have a wide range in the behavior of the charging events. In comparison, in the case of the logistics site, the interquartile range of the idle time is significantly smaller. Overall, the median value of the idle time for the logistics fleet is significantly higher than in the other two cases, i.e., the flexibility to postpone charging processes is noticeably greater for the logistics fleet.

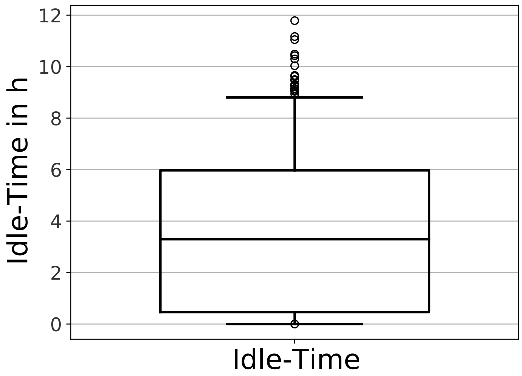

Figure 6. Idle time for the office site.

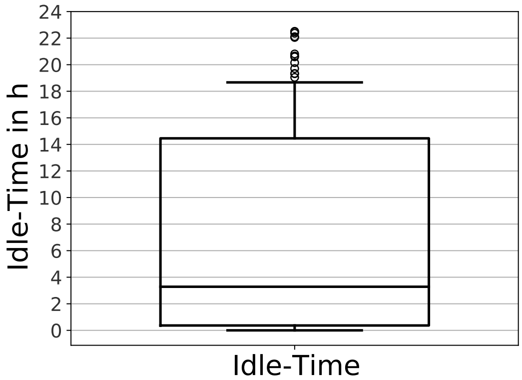

Figure 7. Idle time for the agency site.

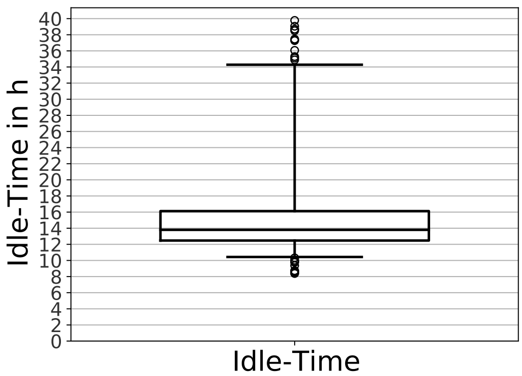

Figure 8. Idle time for the logistics site.

4.2. *Time-Shift-Flexibility*

Time-Shift-Flexibility is the ability to change the charging process within a charging event without affecting the amount of charged energy. $Flex_{\text{shift},k,P}$ (3) shows the Time-Shift-Flexibility potential as a function of different charging rates and indicates how often a charging process would be feasible in terms of time within the associated charging event.

$$Flex_{\text{shift},k,P} = \frac{t_k}{t_{k,P}} \quad k \in \Omega, \tag{3}$$

where t_k describes the duration of the charging event and $t_{k,P}$ represents the duration of the charging process if the real amount of charged energy E_k is charged at charging rate P. For instance, $Flex_{\text{shift},k,P} = 1$ indicates that the whole duration of the charging event is needed to charge the required amount of energy of the corresponding charging event at charging rate P. The charging rate P essentially determines the duration of a charging process. Under a constant amount of charged energy, a higher charging rate leads to a shorter duration of the charging process, whereas a lower charging rate results in a longer duration. If the duration of the associated charging event remains the same, this results in different key figures. In this work, we analyze three different charging rates in more detail:

- Fixed charging rate: $P_{\text{fix}} = 3680\,\text{W}$
- Maximum measured charging rate of the associated charging event: $P_{k,\text{max}}$
- Average charging power of the associated charging process: $P_{k,\text{charging,mean}}$.

The duration of the charging process can be calculated by using Equation (4):

$$t_{k,P} = \frac{E_k}{P} \quad k \in \Omega. \tag{4}$$

Figures 9–11 show the Time-Shift-Flexibility of the individual charging events of the different sites as a boxplot.

The wide dispersion of the $Flex_{\text{shift}}$ of the office site is due to the heterogeneous charging behavior of the site. The range of values of the $Flex_{\text{shift}}$ spans from 0 to 75. Only slight differences in the temporal shift flexibility factor between the average and maximum charging power indicate mainly uncontrolled charging. The fundamentally lower temporal shift flexibility, compared to the other sites, decreases again significantly by the choice of a fixed charging power of 3.68 kW.

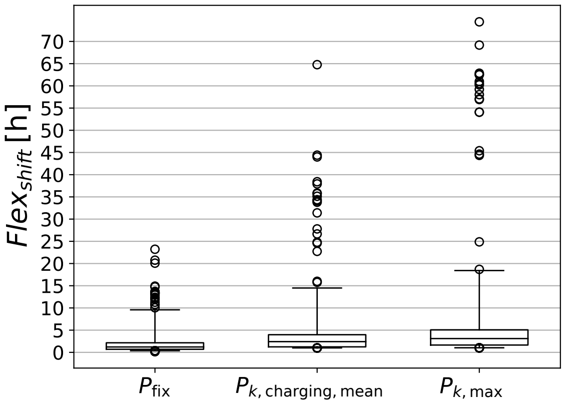

Figure 9. $Flex_{\text{shift}}$ potential for the office site.

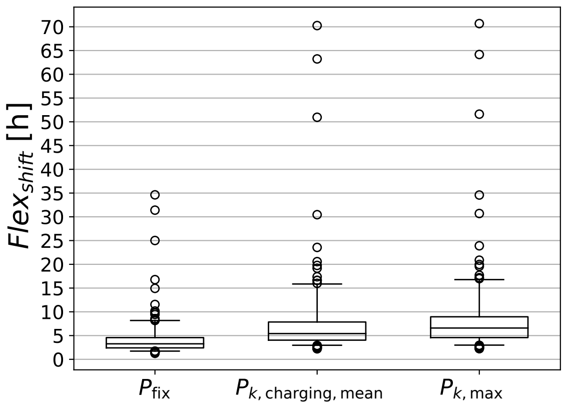

Figure 10. $Flex_{\text{shift}}$ potential for the agency site.

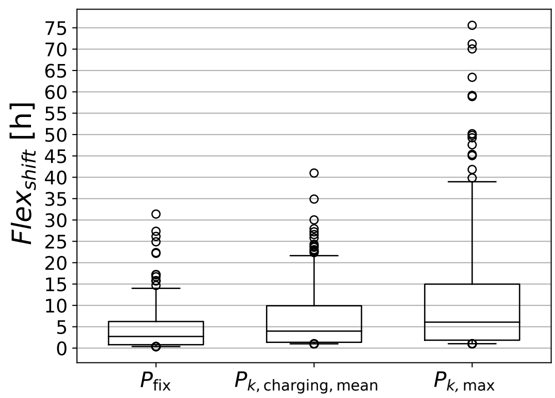

Figure 11. $Flex_{\text{shift}}$ potential for the logistics site.

The Time-Shift-Flexibility factor of the logistics site shows only a small deviation when considering the different charging powers. From this, it can be concluded that the charging processes at this site are carried out with almost maximum charging power. This suggests uncontrolled charging behavior. The Time-Shift-Flexibility factor shows significantly fewer outliers compared to the office site and turns out to be twice as high. Here, there is a direct correlation to the charging station usage and uninterrupted vehicle pairing overnight and on weekends. The long plug-in duration of the vehicles offers a lot of potential to shift the charging processes within the charging event, which was also shown by the idle time. Due to the lower variation in times, a prediction of the potential shift flexibility at this site can be made with a higher degree of reliability. When using the low charging power, the Time-Shift-Flexibility decreases. However, there is still the possibility to perform an average charging operation four times within the corresponding charging event.

The agency site has the greatest Time-Shift-Flexibility. Again, this can be attributed to the lower energy levels, with a longer plug-in duration. When charging with maximum charging power of the charging event, 50 % of the events have a flexibility factor between 3 and 15. The dispersion of the results is higher than that of the logistics site, but smaller than that of the office site. Again, this suggests a diversified user group, with the heterogeneous usage behavior of employee vehicles and homogeneous behavior, due to the company vehicles being combined. The $Flex_{\text{shift}}$ potential at P_{fix} is, on average, equal to that of the logistics site.

The Time-Shift-Flexibility of the different sites is shown in Table 3. These clearly show that, even for charging with a low charging power (P_{fix}), an average charging event has a time shift factor of greater than 2. If the charging power is increased within the range of the physically possible bandwidth, Time-Shift-Flexibility factors of more than 10 can even be achieved. This reflects the enormous potential for controlled charging.

Table 3. Results of the analysis of the Time-Shift-Flexibility of sites at different charging powers.

	Office	**Logistic**	**Agency**
Events	400	260	273
P_{fix} in kW	3.68	3.68	3.68
$\varnothing t_{k,P_{\text{fix}}}$ in h	04:17:37	05:50:43	02:34:53
$\varnothing Flex_{\text{shift},k,P_{fix}}$ in h	2.29	4.14	4.47
$P_{k,\text{charging,mean}}$ in kW	7.69	6.54	6.57
$\varnothing t_{k,P_{k,\text{charging,mean}}}$ in h	02:06:44	03:29:22	01:30:06
$\varnothing Flex_{\text{shift},k,P_{k,\text{charging,mean}}}$ in h	4.35	7.33	6.8
$P_{k,\text{max}}$ in kW	10.08	7.18	9.29
$\varnothing t_{k,P_{k,\text{max}}}$ in h	01:42:12	03:06:03	01:08:17
$\varnothing Flex_{\text{shift},k,P_{k,\text{max}}}$ in h	6.21	8.22	11.24

4.3. FlexBars

Based on Schlund et al. [4], the flexibility of EV charging using FlexBars is visualized below. In the visualization, both the temporal and power-related components are considered. This allows to evaluate the flexibility of a charging event or the average of aggregated charging events of a site at a glance.

FlexBars are constructed as follows: In the horizontal plane, the time is plotted, and the complete width of a FlexBar represents the duration of the charging event. In the vertical direction, the power of the charging event, limited by the maximum possible power, is plotted. The rectangle spanned by the duration of the charging event and the maximum charging power indicates the total possible energy of the charging event. In most cases, this value exceeds the value of the amount of energy to be charged, which results in the flexibility of the charging event.

To consider the flexibility of a site, an average value is calculated over all charging events of the selected analysis period. Figures 12–14 show the FlexBars of the analyzed sites. The dark gray colored areas represent the charged energy amount of the real charging event, each depending on the charging power. The area outside these areas shows the flexibility of the charging—in a horizontal direction in terms of time, and in a vertical direction in terms of charging power.

The FlexBars allow the previously obtained findings of idle time and Time-Shift-Flexibility to be visualized in one figure. In doing so, estimates can be made of both the temporal and power-specific flexibility of the site's average charging event.

The flexibility potential, in both time- and power-specific terms, is enormous for all three sites. The amount of energy charged in real terms is only a small fraction of the amount of the energy possible during the charging event. Furthermore, it becomes clear that, even by lowering the charging power to $P = 3.68\,\mathrm{kW}$, the mobility demand of an average charging event is not affected, and there is still enormous time shifting potential.

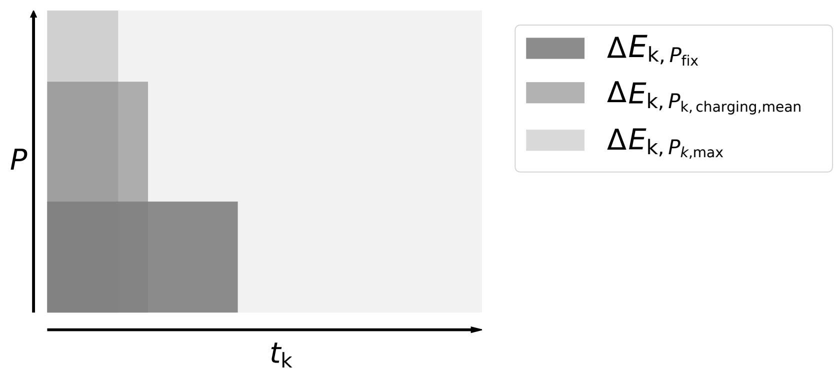

Figure 12. FlexBars for the office site.

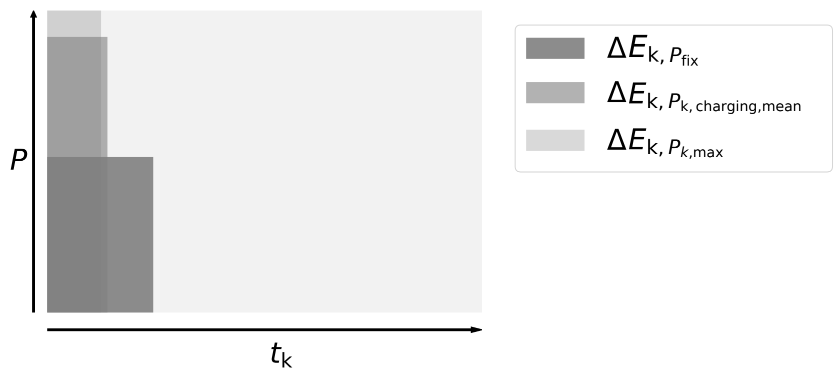

Figure 13. FlexBars for the agency site.

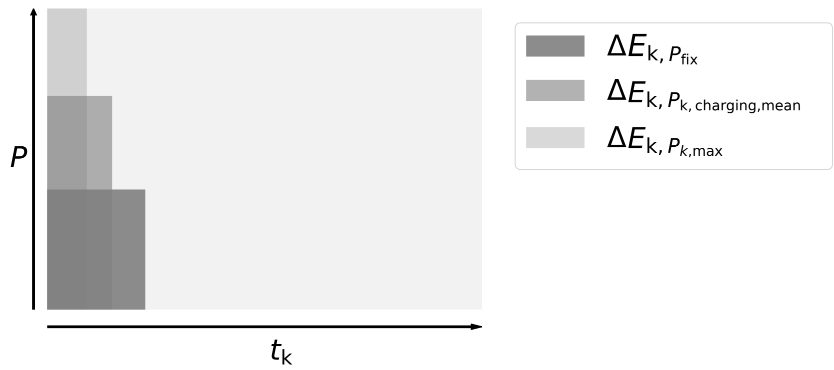

Figure 14. FlexBars for the logistics site.

5. Conclusions

This work addresses the analysis of the charging flexibility behavior of three different electric vehicle fleets. The used input data are based on real-world measured charging events provided through ChargePilot by The Mobility House for a common vehicle fleet of an office, a public authority and a logistics company.

Firstly, we prepared the data accordingly. This included, in particular, the decomposition of the charging events for individual charging points and the subsequent creation of consistency before the charging events could be combined again.

The subsequent analysis shows that the mobility behavior of the three fleets varies greatly, which is also reflected in the charging behavior. Compared to the other fleets, the logistics fleet has a particularly high average plug-in duration and charged energy quantity, while, at the same time, having a low dispersion in the charging events. For all sites, the power curves show characteristic features during uncontrolled charging. For the office and public authority fleet, some of these overlap strongly with common commercial load profiles. Thus, the charging events additionally increase the load peaks and can lead to problems in the supply network. Further investigations would have to be carried out here in future work.

Our analyses of the idle times and shift potential provide important insights into the three vehicle fleets mentioned. Here, we see that the logistics fleet in particular meets the legal requirements in order to be able to exploit the flexibility, accordingly.

In future work, the information gained will be used as a basis for the development of smart energy system services. This helps in exploiting the charging flexibility of different vehicle fleets. For instance, by combining several fleets, it will be possible to participate in control markets.

Author Contributions: Conceptualization, V.B. (Vincent Barthel), J.S., M.P.; methodology, V.B. (Vincent Barthel); validation, V.B. (Vincent Barthel), P.L. and V.B. (Veronika Brandmeier); formal analysis, V.B. (Veronika Brandmeier); writing—original draft preparation, V.B. (Vincent Barthel); writing—review and editing, V.B. (Vincent Barthel), P.L., V.B. (Veronika Brandmeier), M.P., J.S.; supervision, P.L., J.S., M.P.; project administration, P.L., V.B. (Veronika Brandmeier). All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: The authors would like to thank The Mobility House for the data provision and useful discussions.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

RES renewable energy sources
EV electric vehicle
BEV battery electric vehicles

References

1. Edenhofer, O.; Pichs-Madruga, R.; Sokona, Y.; Farahani, E.; Kadner, S.; Seyboth, K.; Adler, A., Baum, I.; Brunner, S.; Eickemeier, P.; et al. (Eds.) *Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2014.
2. Bundesnetzagentur. *Monitoring Report 2019—Key Findings and Summary*; Bundesnetzagentur: Bonn, Germany , 2019.
3. The Mobility House. Charge Pilot—Charging and Energy Management. 2021. Available online: https://www.mobilityhouse.com/int_en/charging-and-energy-management (accessed on 31 May 2021).
4. Schlund, J.; Pruckner, M.; German, R. FlexAbility-Modeling and Maximizing the Bidirectional Flexibility Availability of Unidirectional Charging of Large Pools of Electric Vehicles. In Proceedings of the Eleventh ACM International Conference on Future Energy Systems, Melbourne, Australia, 22–26 June 2020; pp. 121–132.
5. Gerritsma, M.K.; AlSkaif, T.A.; Fidder, H.A.; van Sark, W.G. Flexibility of Electric Vehicle Demand: Analysis of Measured Charging Data and Simulation for the Future. *World Electr. Veh. J.* **2019**, *10*, 14. [CrossRef]
6. Strobel, L.; Schlund, J.; Brandmeier, V.; Schreiber, M.; Pruckner, M. Smart Charging and Renewable Grid Integration—A Case Study Based on Real-Data of the Island of Porto Santo. In Proceedings of the Sustainable Energy for Smart Cities: Second EAI International Conference, SESC 2020, Viana do Castelo, Portugal, 4 December 2020; Springer: Berlin/Heidelberg, Germany, 2021; pp. 200–215.
7. Lee, Z.J.; Li, T.; Low, S.H. ACN-Data: Analysis and Applications of an Open EV Charging Dataset. In Proceedings of the e-Energy 2019: Tenth ACM International Conference on Future Energy Systems, Phoenix, AZ, USA, 25–28 June 2019; Association for Computing Machinery: New York, NY, USA, 2019; pp. 139–149.
8. Khan, S.; Brandherm, B.; Swamy, A. Electric Vehicle User Behavior Prediction using Learning-based Approaches. In Proceedings of the 2020 IEEE Electric Power and Energy Conference (EPEC), Edmonton, AB, Canada, 9–10 November 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–5.
9. Venegas, F.G.; Petit, M.; Perez, Y. Active integration of electric vehicles into distribution grids: Barriers and frameworks for flexibility services. *Renew. Sustain. Energy Rev.* **2021**, *145*, 111060. [CrossRef]
10. Flammini, M.G.; Prettico, G.; Julea, A.; Fulli, G.; Mazza, A.; Chicco, G. Statistical characterisation of the real transaction data gathered from electric vehicle charging stations. *Electr. Power Syst. Res.* **2019**, *166*, 136–150. [CrossRef]
11. Develder, C.; Sadeghianpourhamami, N.; Strobbe, M.; Refa, N. Quantifying flexibility in EV charging as DR potential: Analysis of two real-world data sets. In Proceedings of the 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm), Sydney, Australia, 6–9 November 2016; pp. 600–605.
12. Sadeghianpourhamami, N.; Refa, N.; Strobbe, M.; Develder, C. Quantitive analysis of electric vehicle flexibility: A data-driven approach. *Int. J. Electr. Power Energy Syst.* **2018**, *95*, 451–462. [CrossRef]
13. Lahariya, M.; Benoit, D.; Develder, C. Defining a Synthetic Data Generator for Realistic Electric Vehicle Charging Sessions. In Proceedings of the e-Energy '20: Eleventh ACM International Conference on Future Energy Systems, Melbourne, Australia, 22–26 June 2020; Association for Computing Machinery: New York, NY, USA, 2020; pp. 406–407.
14. Xydas, E.; Marmaras, C.; Cipcigan, L.M.; Jenkins, N.; Carroll, S.; Barker, M. A data-driven approach for characterising the charging demand of electric vehicles: A UK case study. *Appl. Energy* **2016**, *162*, 763–771. [CrossRef]
15. Sørensen, R.; Lindberg, K.; Sartori, I.; Andresen, I. Analysis of residential EV energy flexibility potential based on real-world charging reports and smart meter data. *Energy Build.* **2021**, *241*, 110923. [CrossRef]
16. Sørensen, Å.L.; Lindberg, K.B.; Sartori, I.; Andresen, I. Residential electric vehicle charging datasets from apartment buildings. *Data Brief* **2021**, *36*, 107105. [CrossRef] [PubMed]
17. Rauma, K.; Funke, A.; Simolin, T.; Järventausta, P.; Rehtanz, C. Electric Vehicles as a Flexibility Provider: Optimal Charging Schedules to Improve the Quality of Charging Service. *Electricity* **2021**, *2*, 225–243. [CrossRef]
18. Šikšnys, L.; Pedersen, T.B. Dependency-based FlexOffers: Scalable Management of Flexible Loads with Dependencies. In Proceedings of the e-Energy '16: Seventh International Conference on Future Energy Systems, Waterloo, ON, Canada, 21–24 June 2016 ; ACM: New York, NY, USA, 2016; pp. 11:1–11:13. [CrossRef]
19. Neupane, B.; Šikšnys, L.; Pedersen, T.B. Generation and Evaluation of Flex-Offers from Flexible Electrical Devices. In Proceedings of the e-Energy '17: Eighth International Conference on Future Energy Systems, Hong Kong, China, 16–19 May 2017; ACM: New York, NY, USA, 2017; pp. 143–156. [CrossRef]
20. Boehm, M.; Dannecker, L.; Doms, A.; Dovgan, E.; Filipic, B.; Fischer, U.; Lehner, W.; Pedersen, T.; Pitarch, Y.; Siksnys, L.; et al. Data management in the MIRABEL smart grid system. In Proceedings of the ICDT '12: 15th International Conference on Database Theory, Berlin, Germany, 30 March 2012; [CrossRef]

21. Pedersen, T.B.; Šikšnys, L.; Neupane, B. Modeling and Managing Energy Flexibility Using FlexOffers. In Proceedings of the 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Aalborg, Denmark, 29–31 October 2018; pp. 1–7. [CrossRef]
22. Li, T.; Low, S.H.; Wierman, A. Real-Time Flexibility Feedback for Closed-Loop Aggregator and System Operator Coordination. In Proceedings of the Eleventh ACM International Conference on Future Energy Systems (e-Energy '20), Melbourne, Australia, 22–26 June 2020; Association for Computing Machinery: New York, NY, USA, 2020; pp. 279–292.
23. Sundstrom, O.; Binding, C. Flexible Charging Optimization for Electric Vehicles Considering Distribution Grid Constraints. *IEEE Trans. Smart Grid* **2012**, *3*, 26–37. [CrossRef]
24. Pertl, M.; Carducci, F.; Tabone, M.; Marinelli, M.; Kiliccote, S.; Kara, E.C. An Equivalent Time-Variant Storage Model to Harness EV Flexibility: Forecast and Aggregation. *IEEE Trans. Ind. Inform.* **2019**, *15*, 1899–1910. [CrossRef]
25. Sperstad, I.B.; Degefa, M.Z.; Kjølle, G. The impact of flexible resources in distribution systems on the security of electricity supply: A literature review. *Electr. Power Syst. Res.* **2020**, *188*. [CrossRef]
26. Amini, S.; Pasqualetti, F.; Mohsenian-Rad, H. Dynamic Load Altering Attacks Against Power System Stability: Attack Models and Protection Schemes. *IEEE Trans. Smart Grid* **2018**, *9*, 2862–2872. [CrossRef]
27. Spitzer, M.; Schlund, J.; Apostolaki-Iosifidou, E.; Pruckner, M. Optimized integration of electric vehicles in low voltage distribution grids. *Energies* **2019**, *12*, 4059. [CrossRef]
28. Bons, P.C.; Buatois, A.; Schuring, F.; Geerts, F.; van den Hoed, R. Flexible Charging of Electric Vehicles: Results of a Large-Scale Smart Charging Demonstration. *World Electr. Veh. J.* **2021**, *12*. [CrossRef]
29. Gesetz über die Elektrizitäts- und Gasversorgung: § 14a Steuerbare Verbrauchseinrichtungen in Niederspannung; Verordnungsermächtigung: Energiewirtschaftsgesetz—EnWG, 22.11.2020 (BGBl. I S. 2464). Available online: https://www.gesetze-im-internet.de/enwg_2005/__14a.html (accessed on 25 June 2021).