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Synergy of Unidirectional and Bidirectional Smart Charging of Electric Vehicles for Frequency Containment Reserve Power Provision

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Abstract: Besides the integration of renewable energies, electric vehicles pose an additional challenge to modern power grids. However, electric vehicles can also be a flexibility source and contribute to the power system stability. Today, the power system still heavily relies on conventional technologies to stay stable. In order to operate a future power system based on renewable energies only, we need to understand the flexibility potential of assets such as electric vehicles and become able to use their flexibility. In this paper, we analyzed how vast amounts of coordinated charging processes can be used to provide frequency containment reserve power, one of the most important ancillary services for system stability. Therefore, we used an extensive simulation model of a virtual power plant of millions of electric vehicles. The model considers not only technical components but also the stochastic behavior of electric vehicle drivers based on real data. Our results show that, in 2030, electric vehicles have the potential to serve the whole frequency containment reserve power market in Germany. We differentiate between using unidirectional and bidirectional chargers. Bidirectional chargers have a larger potential but also result in unwanted battery degradation. Unidirectional chargers are more constrained in terms of flexibility, but do not lead to additional battery degradation. We conclude that using a mix of both can combine the advantages of both worlds. Thereby, average private cars can provide the service without any notable additional battery degradation and achieve yearly earnings between EUR 200 and EUR 500, depending on the volatile market prices. Commercial vehicles have an even higher potential, as the results increase with vehicle utilization and consumption.

Keywords: smart charging; electric vehicles; simulation; ancillary services; smart grid

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1. Introduction

The increasing renewable infeed and the aging infrastructure pose major challenges to the operation of EPSs (electrical power systems) all over the globe. In addition, we have recently seen an increased trend in new consumers, such as EVs (electric vehicles), which starts to have a considerable impact on the EPS [1] as well. Forecasts for the worldwide EV stock in 2030 amount to 250 million EVs based on the EV30@30 scenario [2]. If the charging processes of EVs are not coordinated in the future, they will result in a considerable demand peak increase in the evening hours and amplify the problem [3]. Thus, supplying EVs via the EPS brings new challenges [4], but also new opportunities as possible flexibility sources. Due to the high parking duration of privately owned vehicles, EV batteries represent a great flexibility that can be used to support the EPS. For example, renewable energies can be better integrated or ancillary services that were previously provided by conventional power plants can be provided by aggregating many EVs.

A future EPS with highly volatile, uncertain RES (renewable energy sources) and an inflexible demand will not work without extensive grid expansion, large scale storage or other flexibility sources. In this context, flexibility in an EPS is defined as the ability of assets to take different courses of action at a given point in time and thereby provide a service to third parties [5]. However, the energy transition thus far mostly focuses on producing and distributing enough RES, and the system stability itself still depends heavily on conventional technologies.

In the age of digitization, we are able to use ICT (information and communication technology) to pool and actively control the charging processes of many EVs in a VPP (virtual power plant). This has the advantage of charging processes being able to be postponed without restricting the mobility of the user while preserving the electrical grid. The largest part of the charging events will happen at private EVSE (electric vehicle supply equipment) and will be needed for short distance travels [3]. Such EV-charging processes are highly flexible loads [1,6] and are thus theoretically a good source for system-stabilizing ancillary services [7,8]. The tremendous flexibility potential of coordinating charging processes of a large fleet of EVs is also shown by Strobel et al. [9].

In this paper, we analyzed in depth how the smart charging of EVs can contribute to providing FCR (frequency containment reserve) power. For a case study, the German FCR power market serves as an example. FCR power is the fastest and one of the most economically interesting ancillary services in Europe [10]. For the analysis, we utilized a comprehensive and flexible simulation framework that consists of several components, such as a mobility behavior model, flexibility model, and a VPP component. For the case study, we differentiated between unidirectional and bidirectional EVSE and considered stochastic driving behavior based on real data [11,12]. Whereas unidirectional EVSE uses cheaper hardware and does not contribute to additional battery degradation, bidirectional EVSE can provide more flexibility using V2G (vehicle-to-grid). Note that, by ramping the load up and down, it is also possible to provide a bidirectional flexibility service with unidirectional EVSE; it is just more constrained than using V2G-capable EVSE. Subsequently, we aim to combine the advantages of both approaches and provide an analysis of the synergy potential of a mixed approach with only partially V2G-capable EVSE.

The paper is organized as follows: Section 2 presents related work in the field of smart charging of EVs and ancillary service provision. In Section 3, we introduce our methodology by introducing fundamentals about FCR power and our simulation framework. Section 4 discusses results about different cases with regard to uni- and bidirectional charging, as well as a short economical evaluation. We conclude the paper with a short summary and an outlook on future work in Section 5.

2. Related Work

The consideration of smart charging algorithms and the additional use of EV batteries for ancillary service provision has become increasingly important in recent years. As EVs can be seen as a flexible resource, it is important to have an effective and sufficient charging infrastructure. A good overview on the energy and charging infrastructure requirements are given by Thingvad [13]. Literature pertaining to the additional use of EVs for the EPS is often focused on different applications. For instance, Englberger et al. [14] investigated several applications for EV multi-use, such as self-consumption increase, peak shaving, frequency regulation and spot market trading, from a techno-economic point of view. The fleet sizes vary between 1 and 150 vehicles. Results show that the stacking of several services is very profitable with additional cash flows of up to EUR 2224 per EV per year. In this context, the provision of FCR plays an important role and contributes significantly to the annual cash flow. In addition, Tsagkaroulis et al. [15] studied the provision of ancillary services based on real driving data from over 7000 Nissan LEAFs. Based on real data, the authors consider the driving time, distance and parking time at different locations, which constrains the availability of each EV. Under full knowledge of future driving consumption and future grid frequency, an optimization problem is formulated for maximizing the profit of each EV. The profit spreads from EUR 51 to EUR 1654 per year and highly depends on the individual user profiles. In the study by Moncecchi et al. [16], the authors investigated an EV parking garage providing ancillary services in the Italian balancing market. The idea is to adapt the charging rate of the EV to obtain an income from participating on the balancing market. The results show that a large flexibility power can be offered with a high level of reliability.

Due to the increase in EVs as well as other consumers, such as heat pumps, some publications are also focused on the combined delivery of FCR from a fleet of EVs and heat pumps. In the study by Meesenburg et al. [17], the authors present a combined approach of EVs and a large-scale heat pump to exploit the synergies between both systems. The results show that an additional profit from capacity and power price payments can be generated that could not be achieved by the EV or the heat pump alone.

In order to provide ancillary services with a fleet of EVs, the quantification of the flexibility potential and the resulting smart control of charging processes is essential. With regard to the quantification and methodological description of the flexibility potential, numerous approaches can be found in the literature. A review can be found in the dissertation of Schlund [12]. In particular, the FlexAbility concept [18], which is also used in this work, provides a method for modeling the flexibility availability of decentralized electrical loads (e.g., charging processes of EVs). Similar approaches can also be found in [19,20]. Knowledge of the flexibility of charging processes can be used to shift them within the plug-in duration under the usage of smart charging algorithms.

There are many different approaches to the smart charging of EVs that have been published in recent years. For this purpose, many different approaches, such as linear programming, mixed-integer linear programming, model predictive control and machine learning techniques, are used. The optimization goals are a cost reduction from the customer's point of view, a minimization of greenhouse gas emissions, and the best possible integration of renewable energies into the grid. For instance, in the study by Hussain et al. [21], the authors developed a two-layer decentralized charging approach for residential EVs based on fuzzy data fusion. Therefore, they presented a fuzzy integer linear program and showed that the charging costs for EVs can be reduced while guaranteeing their required energy by determining the optimal charging schedule. A optimization-based coordination is also presented by Spitzer et al. [22]. They analyzed the impact of uncoordinated as well as optimization-based coordination strategies on a low-voltage grid. For the optimization-based coordination, they defined three strategies: a cost-optimized, a valley-filling-optimized and a greenhouse-gas-emission-optimized strategy. Depending on the objective, the costs can be reduced by more than 50% and the greenhouse gas emissions by around 40%. Tuchnitz et al. [23] presented a charging coordination system based on reinforcement learning. In contrast to optimization-based charging strategies, general parameters such as arrival times or the parking duration do not have to be known beforehand. The results show that the developed method works very well as all EVs have enough energy for their next trip.

To sum up, there is a large amount of literature available for the ancillary service provision with EVs and the smart control of charging processes. Nevertheless, we identified some research gaps, as some papers omit a deeper comparison of unidirectional and bidirectional charging for the provision of FCR power. Our paper has the following main goals:

- We investigate how unidirectional and bidirectional smart charging can contribute to FCR power provision.
- We are the first to propose and analyze the advantages of a synergistic operation with uni- and bidirectional charging for FCR power provision
- We present a comprehensive and flexible simulation framework.
- We conduct several sensitivity analyses.

3. Methodology

3.1. Frequency Containment Reserve Power

In the European EPS, the nominal power frequency f_0 is 50 Hz and may only vary within ± 0.2 Hz. Therefore, generation and consumption in the whole synchronous EPS need to stay in balance. In order to guarantee this balance, several standardized flexibility services exist. In essence, those services either ramp up or down large amounts of power within certain time constraints. Those services are tendered by the TSO (transmission system operator), which, in Germany, are 50 Hertz Transmission, Amprion, Tennet TSO and TransnetBW.

The FCR power is the flexibility service of highest quality, and the full tendered amount of power needs to be available within 30 seconds. The service is traditionally provided by conventional power plants and, in the recent past, the market became dominated by new players—mostly stationary battery storage systems. In this paper, we analyzed how EVs can theoretically contribute to the service using a simulation model. Thus, we mimicked the requirements from FCR power by equal power manipulations of large amounts of charging processes without constraining the user experience of the vehicle owners. In the following, we summarize the mechanisms of FCR power that are constraining the aggregated power of charging processes when providing the service with a VPP of EVs.

The unit providing the service needs to be able to provide the full reserve power (positive and negative) for at least 15 min at any given time during the contract period [24,25]. The period to be covered per incident is below 15 min [24,25]. The activation begins when the power frequency lies outside the dead band, e.g., of ±10 mHz in the synchronous grid of Continental Europe [26,27]. Then, the FCR power provision increases linearly with an increasing power frequency deviation until a full power provision of the whole contracted power P_{contr} at a power frequency deviation of 200 mHz [26,27].

Thereby, the power difference ΔP to the baseline power of an asset providing FCR power needs to follow the frequency f as defined in Equation (1) [28].

$$\Delta P(f) = \begin{cases} P_{\text{contr}} & \forall\, f < 49.8\ \text{Hz} \\ P_{\text{contr}} \cdot \frac{f_0 - f}{0.2\ \text{Hz}} & \forall\, 49.8\ \text{Hz} \leq f \leq 50.2\ \text{Hz} \\ -P_{\text{contr}} & \forall\, f > 50.2\ \text{Hz} \end{cases} \tag{1}$$

The major challenges to providing FCR power are the requirements of a fast activation time and the required power reservation over a quarter hour [24,25]. The provision is fully symmetric, i.e., an asset providing the service needs to be able to ramp up and down the generation accordingly. The technical feasibility of controlling charging processes of commercially available EVs with a fast enough response time has already been validated by [29]. Thus, the major constraint is the ability of a VPP to reserve power and guarantee the availability over 15 min.

In order to differentiate such an aggregation of flexible loads from a VPP (that typically also includes generation), we will use the term VFP (virtual flexibility plant) in the following. When providing the service with a VPP, the operation follows Equation (1) (counting power generation positively). With a VFP, we are unable to generate power. Thus, we count power consumption positively and follow Equation (2) to provide an equivalent service.

$$\Delta P(f) = \begin{cases} 0 & \forall\, f < 49.8\ \text{Hz} \\ 2 \cdot P_{\text{contr}} \cdot \frac{f - 49.8\ \text{Hz}}{0.4\ \text{Hz}} & \forall\, 49.8\ \text{Hz} \leq f \leq 50.2\ \text{Hz} \\ 2 \cdot P_{\text{contr}} & \forall\, f > 50.2\ \text{Hz} \end{cases} \tag{2}$$

3.2. Simulation Model

We used the discrete events simulation model from [12] to simulate EV fleets of any size. It uses up to 50,000 simulated EV instances that are able to represent up to millions of EVs. The model was implemented in AnyLogic [30], a simulation software based on Java 8 [31]. It uses the framework i7-AnyEnergy [32,33] to implement efficient interfaces between different model components. The model structure is summarized in Figure 1.

The model includes a stochastic component for the social behavior of vehicle owners based on [11]. Behavior in this context means at what time EVs depart or arrive at certain chargers, to which location they drive, how far and fast they drive and how much energy the trips consume. It is important to use realistic driving behavior for our analysis as the behavior essentially poses constraints on the availability of vehicles at the chargers and on the energy amounts that need to be charged. While all this behavior is sampled randomly for individual EV instances, we assumed that the resulting constraints are known to the central VFP controller.

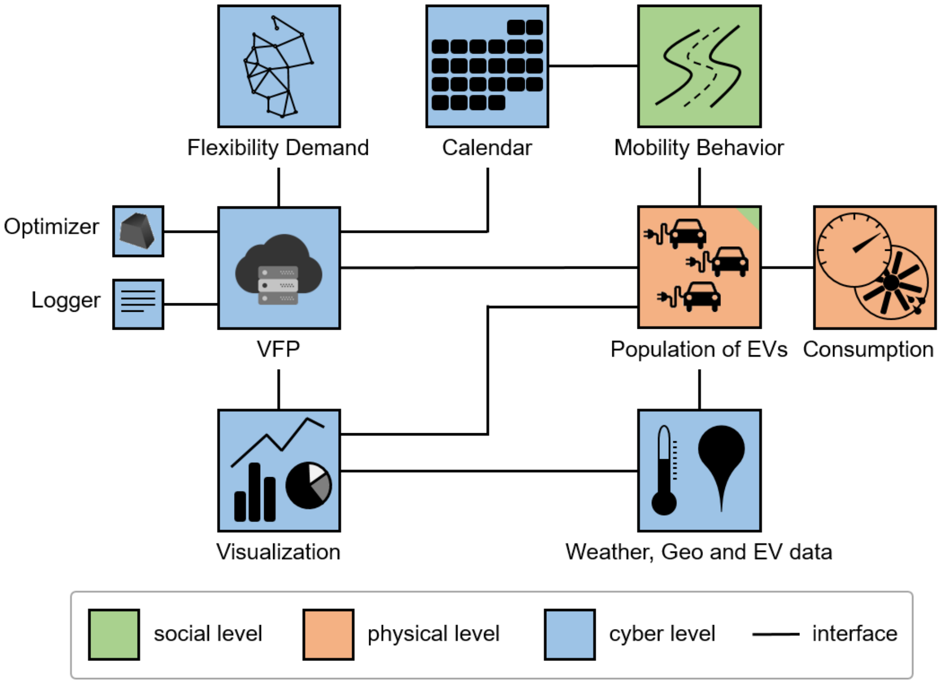

Figure 1. Overall simulation model structure: objects of the different levels and interfaces [12].

The used stochastic mobility behavior model was based on a Bayesian network. Its key assumptions are that EVs are only adopted at mass scale if users do not have to change their behavior and that they mainly charge where they park. It models the mobility patterns, including a correct overnight stay behavior, without any magic rules or numbers, and just based on the input data from [11]. Thereby, the directed acyclic graph structure ensures that the most important variable inter-dependencies are adhered to.

The model describes the daily mobility activity of a vehicle with individual trips between abstract locations (such as *Work*, *Business*, *Leisure*, *Home*, *Education* or *Shopping*). A trip chain then describes the full mobility behavior over a day. It includes all individual constraints of each trip (such as *arrival time*, *departure time*, *duration*, *speed*, *stay time*, *distance* or *purpose*). It can represent patterns of different user groups (*behaviorally homogeneous groups*, *mobility groups* or *age groups*) on different days (the different days of the week and holidays) and locations (different regional types from urban to rural and federal states in Germany). A Python re-implementation of the mobility model component is publicly available on GitHub (https://github.com/jsschl/ev_mobility_model, accessed on 2 September 2022).

On the physical level, we used empirical models of the technical components [12,34], such as battery, on-board charger, HVAC (heating, ventilation, air conditioning) and other consumers, to represent the consumption while driving and the losses while charging. Each simulated EV instance obtains trip chains assigned by the mobility model and then drives accordingly, and is assumed to be available for smart charging whenever it is located at a charger. Thereby, the main charging locations can be varied for different shares between expected amounts at home and workplaces [35].

On the cyber layer, we modeled the cloud-based IT system that is in charge of smart charging control. The VFP connects to the chargers, aggregates the data and combines them with different third party data integration, such as vehicle telematics, weather or geographic data. It is connected to an optimizer that can use different smart charging strategies and algorithms [12] to realize the smart charging application. The model includes a visualization component for fast prototyping and experimentation.

For the use case of FCR power provision, the flexibility demand component represents the requirement of a guaranteed reservation of the full contracted power over 15 min. The VFP uses the FlexAbility model from [12,18] based on the time flexibility [36] to exactly quantify the possible power reservation over an arbitrary time horizon, e.g., 15 min for FCR power provision, at any given point in time. Thus, in order to quantify the potential of FCR power provision with unidirectional chargers, we simulated replications of whole years of operation of a fleet of 5000 EVs and quantified the reservation capability of the overall EV fleet.

Thereby, we firstly considered a baseline scenario with distributions of typical car users and average EV type distributions based on the registration figures in Germany [37,38] and the technical data of the most common EV types [39]. Secondly, we varied certain parameters, such as the battery size of the vehicles, to determine the sensitivity of the results. In the last step, we derived results for mixed fleets with a share of V2G-capable chargers and analyzed the synergy.

4. Results

4.1. Unidirectional Charging

Figure 2 summarizes the sensitivity of key results to key parameters for a fleet size of 5000 EVs in Germany with unidirectional charging only. Note that the points on the y-axes represent simulation results based on the baseline parameterization. As explained above, this baseline parameterization represents the current distribution of technical, social and spatial parameters for EVs in Germany today. The lines on the graphs represent scenarios, where all parameters are kept at the baseline parameterization apart from the parameter that is varied on the x-axis.

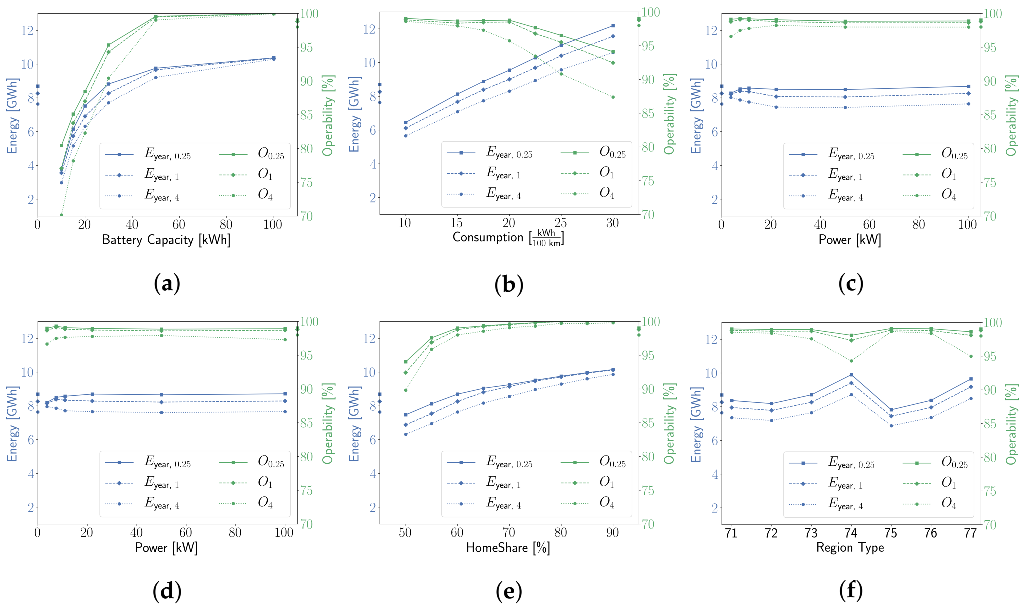

Figure 2. Sensitivity analysis of $E_{\text{year},x}$ (blue) and O_x (green) for key parameters with the default parameterization marked on the y-axes [12]. (**a**) Battery capacity. (**b**) Consumption. (**c**) Max. EV charging power. (**d**) Max. EVSE power. (**e**) Charging at home vs. work. (**f**) Regional type [40].

The results are linearly scalable for large fleet sizes (i.e., larger than 1000 EVs) as the stochastic behavior levels out [12]. The energy flexibility $E_{\text{year},\,x}$ (blue) describes the total power over time horizon x in hours, i.e., energy, that can be reserved over the year. The operability O_x (green) describes the share of the year in which the VFP is able to provide the service. Note that the points on the blue and green y-axes represent the according values for the mixed parameterization in Germany based on the current figures, whereas the points in the graphs and the interpolated lines describe the sensitivity to the given parameter. For these points, the parameters of interest were all set to the given value for all EVs in the simulation.

For the current requirement of $x = 0.25$ in Germany, an operability of over 99% is reached and, on average, a vehicle can contribute 1.75 MWh of reserved bidirectional energy flexibility. For larger time horizons x, these values drop slightly. Without V2G, it is thus possible to provide roughly 200 W per average private car (including the constraint of a full bidirectional reservation over 15 min) over the whole year.

We observe the highest sensitivity to the battery capacity, the consumption and the regional type. The sensitivity to the battery capacity in Figure 2a saturates at large capacities and, interestingly, the current mixed parameterization reaches results that are already close to the maximum. Thus, a fleet with different kinds of battery sizes seems to have synergistic effects.

For the consumption in Figure 2b, we observe that the potential generally increases the larger the consumption is. The reason for this is that the service is generally upper bounded by the ability to decrease the load. A higher consumption means a higher average load and thus also more potential to decrease the load. However, for larger values than 20 kWh per 100 km, the operability decreases significantly as large amounts of charge become necessary, and the reduction in the load is no longer possible throughout certain time periods.

The maximum EV and EVSE charging powers in Figure 2c,d do not show significant sensitivities. This means that the maximum charging powers are large enough in any case and do not pose a constraint to the investigated service. However, as shown in Figure 2e, the location of the main charging stations has a significant effect. It is generally favorable to include a larger share of users that primarily charge at home. Lastly, Figure 2f shows that the potential is generally higher in town and village areas with larger distances (types 74 and 77 [40]). This has the same reasons as described above for the consumption. Other investigated parameters, such as the weather year or the federal state, did not show a notable sensitivity. Even the plug-in behavior of the users does not influence the results considerably, as long as the operational strategy of the VFP is adapted accordingly.

With the knowledge of the sensitivity, an aggregator can compose an optimized fleet for the service. The result improves considerably if the aggregator targets users that live in towns and villages in urban regions and users that have EVs with larger batteries (50 kWh) and a slightly above average consumption ($0.2\,\frac{\text{kWh}}{100\text{ km}}$). In addition, the aggregator should aim at 90% of users that are primarily charging at home. In this specific case, the yearly 0.25 h energy flexibility increases to 2.94 MWh per EV (+69% in comparison to the default case) at an operability of one. This results in an average possible provision of 336 W of FCR power per EV during the whole year.

4.2. Uni- and Bidirectional Charging

Including a certain amount of bidirectional V2G-capable EVSE can improve these results considerably without actually having to discharge any notable amounts during operation. The major constraint for FCR power provision is the reservation and not the actual operation. This becomes clear when observing how the actual power frequency is typically distributed. Figure 3 visualizes a typical power frequency distribution measured second-by-second over a whole year. The power frequency varies in both directions from the nominal power frequency, i.e., a dispatch in both directions is necessary. The measurements follow a Gaussian distribution and the most extreme deviations are considerably below $\pm$100 mHz. A very large proportion of the observations are even within the deadband. In general, the actual observations are only within a very narrow area around f_0, which means that a full provision of the contracted power is never necessary.

If we operate a VFP with unidirectional charging only, the VFP is idle, i.e., neither charging nor discharging, at a frequency of 49.8 Hz (see Equation (2)). Thus, in the whole frequency band of 49.8 Hz to 50.2 Hz, the VFP always charges. It charges more power or less power depending on the frequency, but never discharges the EV.

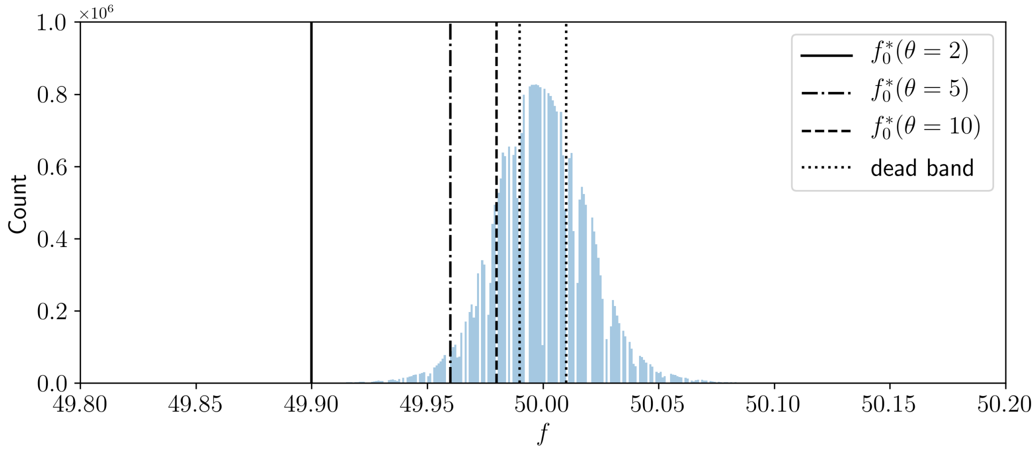

Figure 3. Power–frequency histogram based on second-by-second measurements from [41].

With a VPP of bidirectional chargers only, we can operate symmetrically around f_0 according to Equation (1). This means that the VPP is idle at f_0 (=50 Hz). It charges in the upper half of the frequency spectrum and discharges in the lower half. As the distribution is mostly symmetric, we also roughly need to discharge half of the time.

When we combine unidirectional and bidirectional charging, we can shift this frequency with an idle operation between 49.8 Hz and f_0. This way, it is possible to contract higher amounts of power than with unidirectional charging only, as parts of the flexibility spectrum are covered by discharging. We call the frequency at which we operate in idle mode f_0^*. For instance, with a configuration of f_0^* = 49.9 Hz, the spectrum below 49.9 Hz is covered by discharging and the spectrum above is covered by charging. However, there are typically no or almost no observations below 49.9 Hz. Thus, we can use the discharging capability of V2G for reservation purposes but actually operate in charging mode all or most of the time. This is interesting as additional battery degradation only occurs if EVs are actually discharged.

When we assume that (a) the baseline charging operation is, on average, 200 W per EV and that (b) we are able to contract ten times this amount for FCR power provision when the EVSE has V2G capability (P_{contr} = 2 kW), a discharge is only necessary if the power frequency is at least 20 mHz below the nominal frequency f_0 of 50 Hz. The reason for this is that, in the given scenario, the VFP has a baseline consumption of 200 W and thus only needs to discharge when the frequency f is lower or equal to 49.98 Hz (see Equation (1)).

The over-subscription θ describes the ratio of contracted power P_{contr} to the average possible contracted power only with G2V (grid-to-vehicle) $P_{\text{contr}}^{\text{G2V}}$. It is defined in Equation (3). In the given example above, $P_{\text{contr}}^{\text{G2V}}$ is 200 W per EV, P_{contr} is 2 kW per EV and the over-subscription θ is ten. As defined in Equation (4), the frequency $f_0^*(\theta)$ is then the minimal frequency that does not yet result in a discharge of the VFP. In the example above, $f_0^*(10)$ is 49.98 Hz.

$$\theta = \frac{P_{\text{contr}}}{P_{\text{contr}}^{\text{G2V}}} \tag{3}$$

$$f_0^*(\theta) = f_0 - \frac{0.2\ \text{Hz}}{\theta} \tag{4}$$

Thus, the frequency $f_0^*(\theta)$ describes at which frequency the overall VFP is in idle operation, i.e., neither charging nor discharging. Thereby, θ is the factor of how much more power is contracted in comparison to the scenario without V2G. Without V2G, $f_0^*(\theta = 1)$ needs to be 49.8 Hz as the system needs to be able to provide a full power reduction without being able to discharge. With a share of 10 % and, respectively, 40 % V2G, this frequency can be shifted further to the right and a θ of 2 (without any discharging in operation) and, respectively, 5 (with just very rare occasions of discharging) can be reached.

4.3. Economical Evaluation

Overall, the expected amount of 6.2 million EVs in Germany in 2030 [42] has, in any scenario, the theoretical potential to supply the whole FCR power market of 562 MW [43]. The current coalition contract of the German government even aims at 15 million EVs in 2030 [44], which means an even larger potential. The total costs for this market amounted to EUR 64.5 million in 2018 [25]. Nonetheless, an economic evaluation is difficult due to the recent price volatility, where we have seen prices per MW and week between EUR 1000 and EUR 10,000 [45]. Assuming prices between EUR 2000 and EUR 5000, a V2G share of 35%, which results in a θ of 4.46, and a provision of 1.5 kW per EV, an average EV can achieve earnings between EUR 200 and EUR 500. In this scenario, the necessary average discharge in operation only results in additional battery degradation equivalent to driving 40 km per year, which can be neglected. In comparison, previous research [46] concluded with an additional equivalent aging of driving 1573 km per year and a vehicle for the exact same use case, with bidirectional charging that operates symmetrically around f_0.

5. Conclusions

In conclusion, providing FCR power with EVs generally has a high potential from a technical perspective. The economical feasibility is uncertain but looks promising, with potential yearly earnings between EUR 200 and EUR 500. This can become even more interesting in the future, especially with the recent price increases on the market.

Using the synergy between unidirectional EVSE and V2G-capable EVSE combines the advantages of both technologies, and larger amounts of flexibility can be offered without causing additional charging cycles and battery degradation through discharging during operation. The discharging capability is mostly used for reservation purposes for very rare events, and most of the operation is covered by charging only.

Lastly, follow-up studies with a focus on different commercial vehicles are promising, as the potential for FCR power provision increases considerably with the consumption and utilization of the vehicles. Additionally, weaker stochastic effects in commercial setups simplify real-world applications.

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Abbreviations

The following abbreviations are used in this manuscript:

EPS	electrical power system
EV	electric vehicle
EVSE	electric vehicle supply equipment
FCR	frequency containment reserve
G2V	grid-to-vehicle
HVAC	heating, ventilation, air conditioning
ICT	information and communication technology
RES	renewable energy sources
TSO	transmission system operator
V2G	vehicle-to-grid
VFP	virtual flexibility plant
VPP	virtual power plant

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