

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

Jonas Schlund¹, Marco Pruckner²

¹*Ampcontrol.io, USA, jonas@ampcontrol.io*

²*University of Würzburg, Germany, marco.pruckner@fau.de*

Executive Summary

Besides the integration of renewable energies, electric vehicles pose an additional challenge to the power grid. However, they can also be a flexibility source and contribute to the power system stability. In this paper, we analyze how vast amounts of coordinated charging processes can be used to provide frequency containment reserve power. Therefore, we use an extensive simulation model that considers not just technical components but also stochastic behavior 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 and conclude that using a mix 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 200 € and 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, smart grid, simulation, IoT (Internet of Things), BEV (battery electric vehicle)

1 Introduction

The increasing renewable infeed and the aging infrastructure pose major challenges to the operation of electrical power systems (EPSs) all over the globe. In addition, we recently see an increased trend to electric vehicles (EVs), which start 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 future, they will result in a considerable demand peak increase [3]. Thus, supplying EVs via the EPS brings new challenges [4], but also new opportunities as possible flexibility sources.

A future EPS with highly volatile, uncertain renewable energy sources (RES) 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 so far mostly focuses on producing and distributing enough RES and the system stability itself is still depending heavily on conventional technologies.

In the age of digitization we are able to use information and communication technology (ICT) to pool and actively control charging processes of many EVs in a virtual power plant (VPP). The largest part of

the charging events will happen at private electric vehicle supply equipment (EVSE) 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].

In this paper we analyze in depth how smart charging of EVs can contribute to provide frequency containment reserve (FCR) power at the example of the German FCR power market. FCR power is the fastest and one of the most economically interesting ancillary services in Europe [9]. Thereby, we differentiate between unidirectional and bidirectional EVSE and consider stochastic driving behavior based on real data [10, 11]. While unidirectional EVSE uses cheaper hardware and does not contribute to additional battery degradation, bidirectional EVSE can provide more flexibility using vehicle-to-grid (V2G). Note, that by ramping up and down the load 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.

2 Methodology

2.1 Frequency Containment Reserve Power

In the European EPS the nominal power frequency f_0 is 50 Hz and it may only vary within ± 0.2 Hz. Therefore, generation and consumption in the whole synchronous EPS need to stay in balance. The FCR power is of highest quality and full power needs to be available within 30 seconds. The unit providing the service needs to be able to provide the full reserve power (positive and negative) for at least 15 minutes at any given time during the contract period [12, 13]. The period to be covered per incident is below 15 minutes [12, 13]. The activation begins when the power frequency lies outside the dead band, e.g., of ± 10 mHz in Continental Europe (CE) [14, 15]. 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 [14, 15].

Thereby, the power difference ΔP to the baseline power of an asset providing FCR power needs to follow the frequency f as defined in Eq. 1 [16].

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

The major challenges to provide FCR power are the requirements of a fast activation time and the required power reservation over a quarter hour [12, 13]. 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 [17]. Thus the major constraint is the ability of a VPP to reserve power and guarantee the availability over 15 minutes. In order to differentiate such an aggregation of flexible loads from a VPP (that typically also includes generation), we will use the term virtual flexibility plant (VFP) in the following.

2.2 Simulation Model

We use the discrete events simulation model from [11] 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 is implemented in AnyLogic [18], a simulation software based on Java 8 [19]. It uses the framework i7-AnyEnergy [20, 21] to implement efficient interfaces between different model components. The model structure is summarized in Fig. 1.

The model includes a stochastic component for the social behavior of vehicle owners based on [10]. The used stochastic mobility behavior model is 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, just based on the input data from [10]. Thereby the directed acyclic graph structure ensures that the most important variable inter-dependencies are adhered.

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

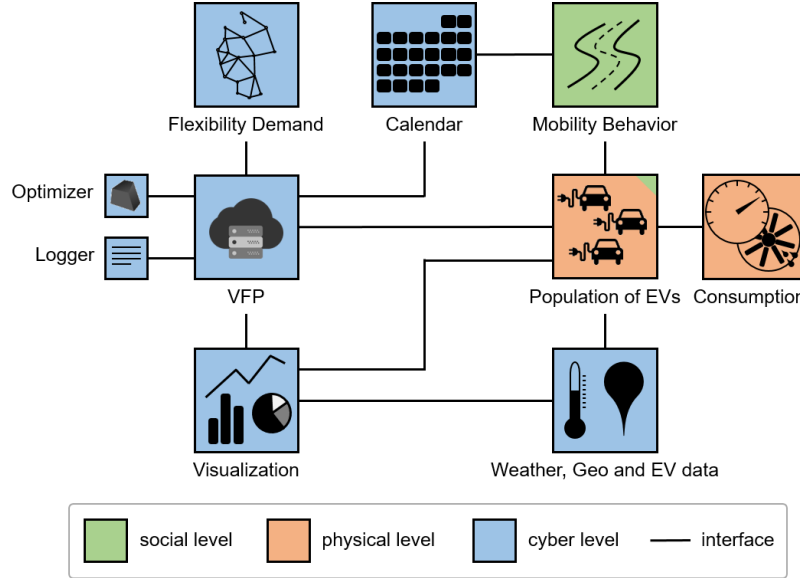


Figure 1: Overall simulation model structure: objects of the different levels and interfaces [11]

federal states in Germany). A Python re-implementation of the mobility model component is publicly available on GitHub¹.

On the physical level, we use empirical models of the technical components [11, 22] such as battery, on-board charger, acclimatization and other consumers to represent the consumption while driving and the losses while charging. Each simulated EV instance gets 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 [23].

On the cyber layer we model the cloud based IT system that is in charge of smart charging control. The VFP connects to the chargers, aggregates the data and combines it 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 [11] 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 minutes. The VFP uses the FlexAbility model from [11, 24] based on the time flexibility [25] to exactly quantify the possible power reservation over an arbitrary time horizon, e.g., 15-minutes for FCR power provision, at any given point in time. Thus, to quantify the potential of FCR power provision with unidirectional chargers we simulate replications of whole years of operation of a fleet of 5,000 EVs and quantify the reservation capability of the overall EV fleet.

Thereby, we firstly consider a baseline scenario with distributions of typical car users and average EV type distributions based on the registration figures in Germany [26, 27] and the technical data of the most common EV types [28]. Secondly, we variate certain parameters, like the battery size of the vehicles to determine the sensitivity of the results. In a last step we derive results for mixed fleets with a share of V2G capable chargers and analyze the synergy.

3 Results

3.1 Unidirectional Charging

Fig. 2 summarizes the sensitivity of key results to key parameters for a fleet size of 5,000 EVs in Germany with unidirectional charging only. The results are linearly scalable for large fleet sizes (i.e., larger than 1,000 EVs) as the stochastic behavior levels out [11]. 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, while the points in the graphs and the interpolated lines describe

¹https://github.com/jsschl/ev_mobility_model

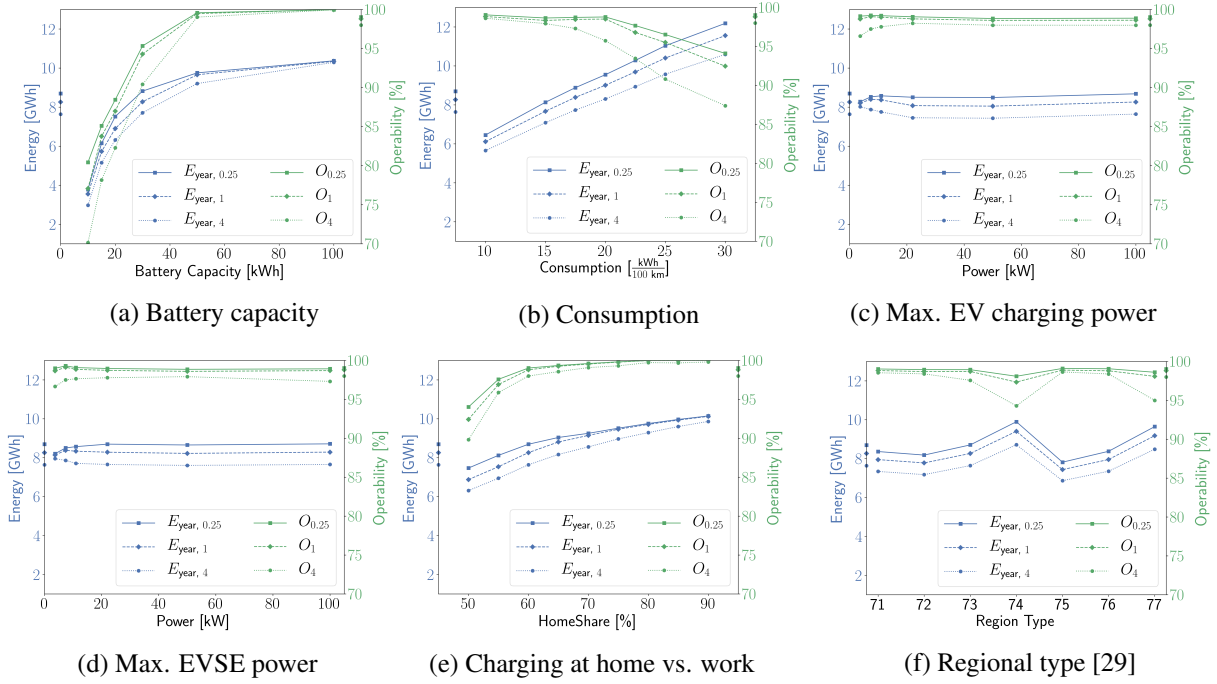


Figure 2: Sensitivity analysis of $E_{\text{year}, x}$ (blue) and O_x (green) for key parameters with the default parameterization marked on the y-axes [11]

the sensitivity to the given parameter. For these points, the parameters of interest are 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 in 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 minutes) 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 Fig. 2a saturates at large capacities and interestingly the current mixed parameterization reaches already results close to the maximum. Thus, a fleet with different kinds of battery sizes seems to have synergistic effects.

For the consumption in Fig. 2b we observe that the potential generally increases the larger the consumption is. The reason for this is that the service is generally upper bound by the ability to decrease load. Higher consumption means 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 of load is no longer possible throughout certain time periods. The maximum EV and EVSE charging powers in Fig. 2c and Fig. 2d 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 Fig. 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, Fig. 2f shows that the potential is generally higher in town and village areas with larger distances (types 74 and 77 [29]). This has the same reasons as described above for the consumption. Other investigated parameters like 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 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 % users that are primarily charging at home. In this specific case the yearly 0.25-hour 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.

3.2 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 is the reservation and not the operation as visualized in Fig 3. It visualizes a typical power frequency distribution. The nominal power frequency varies in both directions, i.e., a dispatch into both directions is necessary. However, depending on the configuration, it is nevertheless most of the time not necessary to discharge. This is interesting as additional battery degradation only occurs if EVs are actually discharged.

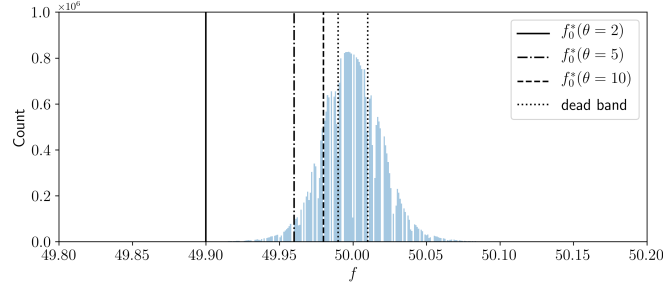


Figure 3: Power frequency histogram based on second-by-second measurements from [30]

When we assume that a) the baseline operation is in 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 ($P_{\text{contr}} = 2$ 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 Eq. 1).

The over subscription θ describes the ratio of contracted power P_{contr} to the average possible contracted power only with grid-to-vehicle (G2V) $P_{\text{contr}}^{\text{G2V}}$. It is defined in Eq. 2. 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 Eq. 3, 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.

$$\theta = \frac{P_{\text{contr}}}{P_{\text{contr}}^{\text{G2V}}} \quad (2)$$

$$f_0^*(\theta) = f_0 - \frac{0.2 \text{ Hz}}{\theta} \quad (3)$$

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 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 % respectively 40 % V2G this frequency can be shifted further to the right and a θ of 2 respectively 5 can be reached.

3.3 Economical Evaluation

Overall the expected amount of 6.2 million EVs in Germany in 2030 [31] has in any scenario the theoretical potential to supply the whole FCR power market of 562 MW [32]. The total costs for this market amounted to 64.5 million € in 2018 [13]. Nonetheless, an economic evaluation is difficult due to the recent price volatility where we have seen prices per MW and week between 1,000 € and 10,000 € [33]. Assuming prices between 2,000 € and 5,000 €, 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 200 € and 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 [34] concluded with additional equivalent aging of driving 1,573 km per year and vehicle for the exact same use case with bidirectional charging that operates symmetrically around f_0 .

4 Conclusion

In conclusion, providing FCR power with EVs has generally a high potential from a technical perspective. The economical feasibility is uncertain but looks promising, 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 purpose for very rare events and most 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 the utilization of the vehicles. Additionally, weaker stochastic effects in commercial setups simplify real world applications.

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Presenter Biography



Dr.-Ing. Jonas Schlund has a M.Sc. in energy technologies and a PhD in computer science focusing on modeling, simulation and optimization of smart charging of electric vehicles. He worked as a researcher in the smart energy group at the lab for computer networks and communication systems at University of Erlangen-Nuremberg. He has professional experience in machine learning, data science, SaaS, IoT applications, battery technology and energy automation at both, startups and industry leaders like Siemens or Seat. Currently he leads the data science team of Ampcontrol.io, a New York based SaaS startup providing optimization technology for electric vehicles.