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Optimal pool composition of commercial electric vehicles in V2G fleet operation of various electricity markets

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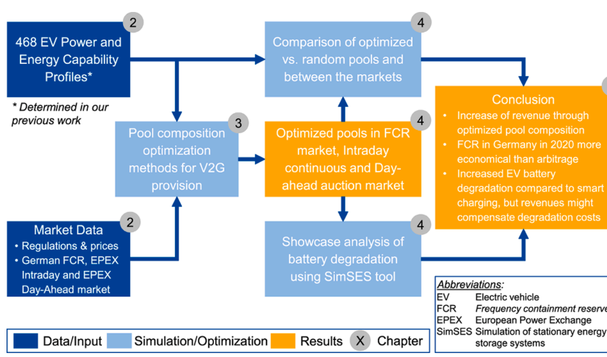
HIGHLIGHTS

- Methodology to optimize commercial EV pool composition for V2G services.
- Simulation of EV pooling to provide balancing power (FCR) and arbitrage trading.
- Optimized pool composition enables an increase in revenue per EV of up to 7-fold.
- Showcase analysis of battery-specific costs arising from degradation in V2G.

GRAPHICAL ABSTRACT



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ABSTRACT

The market ramp-up of electromobility is shifting vehicle-to-grid (V2G) issues into the focus of research and industry. Electric vehicles (EVs) have the potential to support the trend towards renewable energies in their role as storage units during idle times. To participate in balancing power and energy markets, EVs are pooled via aggregators. Instead of a random composition, aggregators can smartly compose their pools and add only those vehicles that actually contribute to the pool's performance, gaining advantages over competitors. The optimization methods presented in this paper form optimized pool combinations based on the power and energy capability profiles of commercial EVs. Genetic algorithms are used to determine the revenues of the possible pools per participating EV. The use cases analyzed are the provision of balancing power on the frequency containment reserve (FCR) market of Central Europe and energy arbitrage trading on the European power exchange intraday continuous and day-ahead auction spot markets. The results show that through smart pool composition, an aggregator can increase revenue per vehicle by up to seven-fold across the markets compared to randomly assembled pools. In the Central European market, for example, the potential V2G revenues on the FCR market (380 €) exceeded those of arbitrage trading (28 € – 203 €) in 2020. In a simulation, we show the

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increased degradation of the vehicle battery in V2G operation compared to sole use for mobility with a smart charging strategy. However, the additional revenue can make V2G financially worthwhile, depending on costs for measuring equipment, bidirectional charging stations, and aggregator costs.

Abbreviations

BSS	Battery storage system
BTM	Behind-the-meter
CESA	Continental European Synchronous Area
EEX	European Energy Exchange
EFC	Equivalent full cycles
ENTSO-E	European Network of Transmission System Operators for Electricity
EOL	End of life
EPEX	European Power Exchange
ERCOT	Electric Reliability Council of Texas
EV	Electric vehicle
FCR	Frequency containment reserve
FTM	Front-of-the-meter
GA	Genetic algorithm
NACE	European Classification of Economic Activities
NMC	Nickel-Manganese-Cobalt
PGS	Institute for Power Generation and Storage Systems
RQ	Research question
RWTH Aachen University	Rheinisch-Westfälische Technische Hochschule Aachen
SimSES	Simulation of stationary energy storage systems
SOC	State-of-charge
SOE	State-of-energy
TSO	Transmission system operator
V2G	Vehicle-to-grid
WPC	Wasted power capability

1. Introduction

The ongoing shift from conventional, centralized energy producers to renewable, decentralized energy producers in Germany has become known worldwide as the "Energiewende" [1,2]. An ambitious goal now being pursued globally is the transformation of transportation from internal combustion engines to electrically powered vehicles. Worldwide, 10 million EVs were already in use at the end of 2020 [3]. The German government, for example, plans to have 7 to 10 million electric vehicles (EV) on German roads by 2030 [4]. The vehicles' storage capacities offer an exceptionally large potential: 7 million EVs with an average assumed energy capacity of 50 kWh have a total capacity of 350 GWh. If each EV were connected to the grid with an average power of 11 kW, the maximal total available power would be 77 GW, which corresponds approximately to the maximum electricity demand in Germany in 2019 [5]. Thus, on the one hand, if all EVs charged simultaneously at the time of the peak load, the peak load could double. On the other hand, the EVs could provide power to cover the entire load in Germany for a short time. Since, for example, German private vehicles are parked 97 % of the time, the additional use of vehicles to provide power for the electricity grid in the form of V2G is a promising approach [6]. This additional use of EV batteries can provide economic benefits to the owner through lower total costs of ownership [7]. Furthermore, from a national economic perspective, a higher utilization rate results in a more efficient use of resources. In this context, the use of EVs via V2G could reduce the number of required stationary storage systems [8].

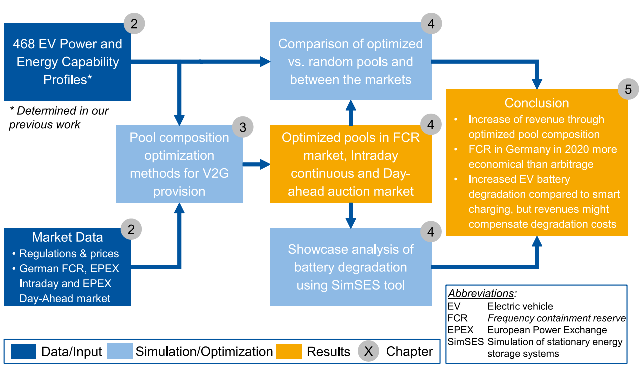

Fig. 1. Graphical overview of this work.

Alongside the concept of second life, or second use, there is another, more recent concept: dual use [9,10]. In dual use, the vehicle is used alternately for mobility and for V2G applications over periods of minutes, hours, and days. The priority here is mobility for the vehicle owner. Only free capacities are used in dual use to serve other applications by means of V2G. The power that an EV can charge and discharge is usually not sufficient to participate in balancing power markets and spot markets. For this reason, aggregators, which bundle the capacities of individual EVs in pools, emerge [11,12]. These so-called virtual power plants can then participate together in those markets [13].

In order to gain competitive advantages, aggregators could assemble their pools as efficiently as possible and not accept vehicles randomly. The optimization methods presented in this paper can help them to assemble their pools in the most efficient way. Knowing the driving profiles of the possible participants, aggregators can use the optimization methods as a basis for assembling their pools in such a way that each participating vehicle actually contributes. Without knowledge of the profiles, aggregators should measure or estimate the EV by known vehicles with similar characteristics before including it in the pool. In this way, the economic attractiveness of potentially adding an EV can be estimated.

Fig. 1 gives an overview of the present work. We used driving data of 468 EVs to determine power and energy capability profiles, that were presented in detail in a previous paper [10]. In this work, we use the profiles together with market data in the optimization methods. The markets considered here are the frequency containment reserve (FCR) market in central Europe, as well as the EPEX day-ahead auction and intraday continuous market. In the optimization, the revenue per participating vehicle of the pool is maximized. Consequently, only vehicles that make an essential contribution to the marketable pool power are included in the pool.

In the following, we first summarize existing literature on V2G and EV fleet operation. Afterwards, we describe the scenario considered in this work.

1.1. Summary of existing literature

Since the turn of the century, the research field of electric vehicles and, in particular, the V2G sub-area has attracted much interest [14,15]. Thereby, it was shown that the use of EVs in electricity markets is

Table 1
Summary of literature about **simulation and optimization** of trading on spot markets with EV fleets.

Source	Date	Focus	Results
Bessa [34]	2011	Optimization of an aggregated EV fleet trading in the Iberian day-ahead market and providing secondary reserve in the Iberian ancillary services market.	- Optimized bidding reduces charging costs compared to naïve charging. - The additional provision of positive and negative secondary reserve is economically even more worthwhile.
Schuller [35]	2014	Simulation and economic comparison of smart V2G vs. smart unidirectional vs. as-fast-as-possible charging considering degradation.	- Smart charging strategies decrease charging costs by a minimum of 32 % (employees' driving profile) to 51 % (retirees' driving profile) in the considered scenario compared to charging the EV as fast as possible. Adding V2G capability leads to reduced costs of 39 % to 45 % (employees driving profile). - V2G can be beneficial, but regulatory incentives are required.
Kiaee [36]	2015	Calculation of possible savings by clever charging of EV including V2G.	- Allowing V2G and using a smart control strategy reduces charging costs by 13.6 % compared to using only unidirectional charging.
Sánchez-Martín [37]	2015	Development of a stochastic programming model to optimize charging process of EV from day-ahead and intraday market and provision of regulating reserves.	- Energy costs for charging EVs can be reduced by 1 % to 15 % depending on price spreads and other characteristics analyzed in case studies.
Shang [38]	2016	Creation of a stochastic optimization model to investigate the profitability of electricity arbitrage with PHEV.	- Owners of PHEVs cannot generate additional revenue through arbitrage when considering battery degradation even when assuming optimistic future costs. - Reducing the costs of battery degradation or combination arbitrage with various applications could make arbitrage trading profitable.
Guo [26]	2017	Development of a bidding strategy for an aggregator of EVs to participate in the day-ahead market.	- Developed bidding strategies improve handling of risks in day-ahead markets. - V2G only worthwhile if costs for discharging and distribution tariff are reduced.
Giordano [27]	2020	Optimization of day-ahead charging of an EV pool developing completely automated aggregator.	- Aggregator costs can be reduced by up to 57 % when applying V2G energy arbitrage in the Italian day-ahead market compared to no V2G without restricting EV users.
Zheng [39]	2020	Optimal bidding strategy in the day-ahead market is developed.	- Stochastic optimization model maximizes aggregator's revenues involving multiple agent modes.

basically possible, but that there are still regulatory restrictions [16,17]. These lead to economic uncertainty regarding possible business cases [14,15]. In addition, increased battery degradation and lack of aggregation concepts were identified as technical barriers to the widespread implementation of V2G in 2017 [14,18]. Here, the increase in degradation depends largely on the energy throughput and is sensitive to the charging strategy, as Bishop et al. discovered in 2013 [19]. Petit et al. showed an increase in degradation in 2016 for LFP and NCA based lithium ion batteries [20].

There are also social obstacles: From the perspective of EV owners, a guaranteed minimum range and their range anxiety are the greatest influencing factors on the willingness to participate in V2G [21,22]. Nevertheless, V2G offers great potential: In recent years, much progress has been made in battery research and battery costs have been gradually reduced [16,23]. In addition, V2G has been tested in many field tests [24,25]. Moreover new aggregator concepts have been developed [26,27]. Therefore, the authors expect V2G to become relevant to a considerable extent in the future.

For the provision of V2G, various electricity and power markets are of interest [16,28]. The focus of this work lies in the FCR market and the participation in European Power Exchange (EPEX) spot markets for arbitrage trading. Other methods sufficiently considered in research are for example the optimized charging of EVs [29,30].

The provision of balancing power using EVs was shown to be feasible in various field tests [24,25]. Moreover, optimization algorithms have been developed to improve performance [31], and economic analyses have been carried out to estimate possible revenue [32,33]. We published an in-depth review of the literature on performing frequency regulation with EVs in our previous work [10].

Two other markets in which pools of EVs can participate are part of the EPEX spot market. The markets analyzed in this paper are the day-ahead auction market and the intraday continuous market used for energy arbitrage. Algorithms that maximize energy arbitrage revenues using stationary battery storage systems (BSSs) have already been developed [40,41]. Others do not only include BSS, but also wind and photovoltaic into virtual power plants optimizing profits from arbitrage trading [42]. According to a study, the profitability of arbitrage trading depends more on technical parameters such as efficiency and self-discharge than on price volatility [43]. Furthermore, the consideration of battery degradation has a major impact on profitability [41]. One study has shown that it can reduce revenues by 12–46% [44]. Another publication analyzing the US American ERCOT market showed that increasing calendar life of lithium-ion BSS provides greater benefits than increasing cycle life while energy arbitrage trading [45].

The pooling of EVs by means of an aggregator also offers the possibility of participating in arbitrage trading [11]. Table 1 gives an extract of publications on simulation and optimization of trading on spot markets with EV fleets sorted by publication year. Several research works showed that optimized bidding in the spot markets reduces charging costs for an EV fleet [35,36] Shang et al. investigated the profitability of arbitrage using plug-in hybrid vehicles and showed that it is not economical considering battery degradation [38]. Giordano et al. showed that using V2G aggregator costs of day-ahead market charging of EV fleets could be reduced without restricting EV owners [27]. Zhou et al. developed scheduling models for EV charging regarding dynamic electricity prices and inconvenience for the EV owners [46].

When using EVs to provide balancing power or arbitrage trading, the uncertainty of vehicle availability should be considered. Therefore, Tuchnitz et al. modeled smart charging strategies by applying reinforcement learning to EV fleets relieving grid congestion [47]. The comparison with optimization-based strategies showed that their strategy could better handle uncertainties such as spontaneous trips. The individual driving behavior of EV owners in the pool determines the total available capacity and power [48]. For example, Han et al. estimated the achievable power capacity of EVs using probability density functions in 2011 [49]. Fluhr et al. developed a stochastic model to estimate the availability of EVs for the provision of grid balancing services [50]. They concluded that at least 90 % of all EVs are parked (anywhere) at all times and more than one quarter is parked at home.

Aside from the optimized bidding strategies and the field tests for providing FCR and arbitrage with EVs, the power capability profiles of individual vehicles have received little to no attention in research. These power capability profiles indicate how much power a vehicle can currently charge or discharge in addition to its primary use, which is

Table 2
Fleet categories and scenario considered in this work (commercial, <50 EVs).

Category	Description	Fleet Size	Example
Private	Cars in private ownership	typically 1-2	Private households
Private + Commercial	Cars used for private and commercial mobility	variable	Employees in field service
Commercial	Company cars	< 50 EV	Small and Medium-sized companies
		> 50 EV	Postal services

Table 3
Market characteristics of the markets considered in this work.

	Frequency containment reserve (FCR) [57]	Intraday continuous market [60]	Day-ahead auction market [60]
Market Direction	ancillary service bidirectional obligatory	energy unidirectional & bidirectional possible (buy or sell)	energy unidirectional & bidirectional possible (buy or sell)
Provision time	15 min (to be activated in < 30 s)	minimum 15 min	minimum 1 h
Time sectioning	4 h	15 min	1 h
Minimal bid	1 MW (Demand in Germany in 2020: 573 MW)	0.1 MW (0.025 MWh)	0.1 MW (0.1 MWh)
Minimal increment	1 MW	0.1 MW	0.1 MW
Remuneration	market-clearing price (power)	pay-as-bid price (energy)	market-clearing price (energy)
Typical price range in 2020	~ 30 €/MW/4h	~ 10–60 €/MWh	~ 20–50 €/MWh
Tendering	8 a.m. (D-1)	from 3p.m.(D-1) up to 5 min before power provision	12 a.m. (D-1)

mobility or its charging [10]. Although driving profiles have received strong attention in the literature and have been analyzed, for example, in [35,51], the clever composition of pools of EVs has not yet been considered in depth. To the best of our knowledge, the targeted inclusion or rejection of vehicles to compose the most efficient vehicle pools for different markets has not been explored in more detail. With our work of optimized pool composition based on capability profiles, we aim to address this research gap. The methods presented can help aggregators to increase their profitability and gain competitive advantages. We consider the FCR market and arbitrage trading on the EPEX Spot markets intraday continuous and day-ahead auction. In detail, we would like to answer the following research questions (RQs) in the course of the paper:

RQ1) Can aggregators of EV pools gain a competitive advantage through smart selection of vehicles? (Section 4.1)
RQ2) How large are potential revenues in various electricity markets for random and for optimized pools? (Section 4.1)
RQ3) Which markets are more interesting: balancing power or arbitrage? (Section 4.1)
RQ4) What is the influence of dual use on battery degradation? (Section 4.2)
RQ5) Could potential revenues from V2G participation cover the cost of additional degradation? (Section 4.2)

1.2. Scenario

Fleets of vehicles generally exist in different sizes. In this work, we distinguish between the categories (1) private households and (2) industries (see Table 2). Private households usually own one or two vehicles, rarely a few more. The size of fleets with vehicles that are used in combination for private and commercial purposes can vary significantly. Commercially used vehicles of small and medium-sized companies form fleets of typically up to 50 vehicles[1]. In contrast, fleets of large companies or companies that operate in the transport or postal sector consist of up to several hundred vehicles. These large fleets can participate independently in power and energy markets because they meet minimum bid sizes. The vehicles considered in this work for dual use are fleets of small and medium-sized companies. For these fleets, a separate participation in electricity markets is only conditionally worthwhile. A smart charging of EVs by trading on the intraday continuous market would be possible, for example. In contrast, arbitrage trading or the provision of balancing power is only possible with larger or combined fleets. Thus, in this work, we combine EVs of these small and medium-sized companies into larger pools of up to 468 EVs.

The optimization methods presented in this work form pools of vehicles based on the power capability profiles of EVs of small and medium-sized companies. The objective is to maximize the revenue per participating vehicle. Thus, the highest possible revenue with the lowest number of vehicles is searched for. Aggregators who are able to forecast the driving profiles of their potential vehicles can use the algorithms presented in this work. Alternatively, aggregators could measure EVs over a period of, for example, two weeks before deciding to include them in the pool. This way, they can only include those vehicles in their pool and equip them with bidirectional charging stations that add value to their pool. Consequently, they would only offer participation in the virtual power plant to these vehicles and would therefore only reward these EVs financially. In contrast, aggregators could blindly assemble their pools. For this reason, we will compare the optimized pools with randomly assembled pools of the same number of vehicles. In principle, total aggregator revenues increase as the number of EVs in the pool increases. Thus, in a large market of possible EVs in the future, aggregators would not limit themselves to the maximum number of 468 EVs used in this work. However, the methodology is also applicable to more EVs leading to higher efficiencies compared to random pool compositions.

Another potential use of the algorithm is the retrofitting of only a few vehicles of large fleets from combustion engines to electric drives. These vehicles to be retrofitted could be selected according to their potential to participate in electricity markets considering their driving profiles.

In this paper, we assume that EVs will be mostly V2G capable in the future. Some car manufacturers, such as Nissan, already sell V2G-capable vehicles [15]. Furthermore, BMW and Renault, for example, are testing V2G in research projects [52,53]. Volkswagen has also announced plans to introduce bidirectional charging for its vehicles [54]. Other stakeholders include transmission system operators that have already recognized the potential of V2G flexibilities and grid support and are planning to adapt market rules accordingly [55].

Furthermore, we first maximize the potential revenues EVs can generate in the various markets. However, the additional degradation costs of the vehicle battery can be significant depending on the control algorithms [18,56]. Degradation of EV batteries has shown to be the greatest concern of EV owners when participating in V2G [21]. Thus, we investigate the additional degradation of the vehicle batteries in dual use using an exemplary driving profile in Section 4.2. In this work, costs for equipping the participating vehicles with smart metering devices and bidirectional charging stations are neglected, since these costs are incurred per vehicle and therefore reduce the revenues per vehicle of optimized pools as well as the random pools equally. After the presentation of the scenario, the following chapter deals with the basic data of the work.

[1] The limit of 50 vehicles is not fixed, but only represents the order of magnitude and separates the categories.

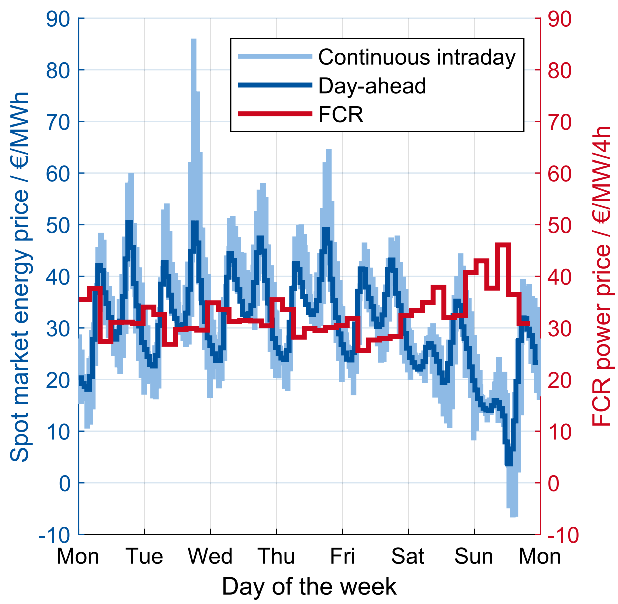

Fig. 2. Average weekly prices in 2020 for a) EPEX intraday continuous (weighted average pay-as-bid price), b) EPEX day-ahead auction (market-clearing price) and c) frequency containment reserve (FCR) provision in Germany (market-clearing price).

2. Database

This chapter describes the database of the present work. For this purpose, Section 2.1 explains the rules of the electricity markets under consideration. In addition, we present and analyze the price data of the markets. Section 2.2 presents the EV data. There, we describe the basis of the driving data and how profiles for the optimal pool composition are obtained from these data.

2.1. Electricity market rules and price data

This chapter presents the three markets identified in the literature research as potential areas of application for EVs. These include the FCR market as an ancillary service market and the two spot markets of (a) the intraday continuous market and (b) the day-ahead auction market. Table 3 provides an overview of the most important market characteristics and Fig. 2 depicts the weekly average prices for all markets. The respective subsections refer to both the characteristics and the price developments. Since this paper does not include bidding strategies, exclusively average prices are discussed.

2.2. Frequency containment reserve market (FCR)

FCR is the fastest of the three frequency regulation types in the Continental European Synchronous Area (CESA). Within the CESA, a total of 3,000 MW of FCR power is reserved, which is distributed among the member states according to generation capacity [57]. In 2020, Germany required 573 MW, which is tendered via the portal of the four transmission system operators (TSOs) as an anonymous tender auction and tendered according to a market-clearing power price [57]. The tendered power must be held in reserve as bidirectional power of an integer multiple of 1 MW for a time section of four hours at a time [57]. However, in accordance with the requirements of the TSOs, the permanent provision of power must only take place for 15 min in a specific call, whereby it must be possible to provide the full power after 30 s [57]. In addition, for limited energy storage such as batteries, a minimum power buffer of 25% of the FCR power must always be maintained [57]. Detailed market and price analyses can be found in [58] and [59]. The average prices were around 30 €/MW/4h in 2020 and Sat-Sun had higher prices than weekdays Mon-Fri (see Fig. 2).

2.3. Intraday continuous market

In the intraday continuous market, energy is traded on a quarter-hourly basis in various block sizes of minimum 15 min [60]. Supply and demand are matched in a pay-as-bid process, resulting in a variety of prices for each quarter hour. The smallest tradable unit of power is 0.1 MW [60], which means that a minimum of 25 kWh can be provided in a quarter hour. The average price shows high volatility; in 2020 average prices of over 80 €/MWh but also negative prices occurred (see Fig. 2). In general, prices ranged predominantly between 10 €/MWh and 60 €/MWh. Further information on the intraday continuous market can be found in [61].

2.4. Day-ahead auction market

On the day-ahead market, participants trade energy hourly in various block sizes of at least one hour for the following day. Unlike the intraday continuous market, supply and demand are matched together in a market-clearing price. The traded power over the traded provision time corresponds to the integer multiple of 0.1 MW [60]. From this value, it follows that the traded energy corresponds to an integer multiple of 0.1 MWh due to the minimum block size of one hour. The hourly-changing price shows less volatility than the intraday curve and was around 20 €/MWh and 50 €/MWh in 2020 (see Fig. 2). Further price information can be found in [61], which also describes the impact of the Covid-19 pandemic.

2.5. Vehicle data and capability profiles

The optimized pool composition requires profiles that describe how much power and energy a vehicle can charge or discharge at any given time. We call these profiles power capability profiles and energy capability profiles, respectively. In a previous paper, we described in detail how the power and capability profiles are determined from vehicle and driving data [10]. In this section, the most important points are briefly discussed. In addition, we explain the formation of intraday and day-ahead profiles.

The basis of this work is two databases: One being measured data from the Institute of Power Generation and Storage Systems (PGS) at RWTH Aachen University in the project “Commercially operated electric vehicle fleets (GO-ELK)” [62]. In this project, data loggers measured 22 EVs. A database from the REM 2030 (regional eco mobility) project was also used [63,64].

Using the vehicle data, we first carried out a statistical evaluation. For this purpose, probabilities for start, duration, and distance were determined over the course of the day and week. Using the statistical data of the vehicles, driving profiles were created in the second step. Afterwards, a simulation model to simulate driving profiles from the probability data was developed. As in our first work, a minimum of 30 % of the capacity is reserved for spontaneous mobility. For the charging process, we used measured charging curves from the PGS at RWTH Aachen University [10].

Weekly driving profiles were simulated for each vehicle. To determine the power and energy capability profiles during parking times, we divided the respective vehicle battery virtually into energy for mobility (primary use) and freely available energy for dual use. This freely available energy over time results in the energy capability profile. The power capability profile indicates the power that a vehicle can charge and discharge at any given time when it is parked at the company site. This power depends on a) the power electronics of the EV, b) the power electronics of the charging station, and c) the available energy and the provision time over which the power must be delivered (depending on the market). Accordingly, the capability profiles for the different markets vary. At the FCR market the provision time is 15 min. The power must therefore be provided over 15 min. The same applies to the intraday market. In the day-ahead market, in contrast, time slices are marked by the hour. This results in different capability profiles for the different markets.

Similar to our previous work, we formed profiles of 468 vehicles from the REM 2030 database. These 468 vehicles meet the following three criteria: a) the vehicle was measured over at least one week, b) the vehicle must make at least one trip, and c) the vehicle must be at the company site at least once. In our previous work, we clustered the power capability profiles according to the economic sectors. In this work, we do not cluster the profiles but use each profile separately.

In the two optimization methods presented in the next chapter, we use both the energy and power capability profiles. For the optimization of the pool composition in the FCR market, the power capability profiles of each vehicle over one week are used. For optimization in the spot markets, the energy and power capability profiles are both used. In the intraday continuous market optimization, 15-minute continuous trading and in the day-ahead auction market, 1-hour auction trading were considered. Due to the different provision times, the power capability profiles for the two markets vary, while the energy capability profiles are the same (see Section 0). In this work, we use weekly profiles because commercial vehicle profiles are relatively constant over a period of months and years.

3. Methodology

In this chapter, we present the methodology of building optimal pool compositions. Section 3.1 deals with the optimization method for balancing power markets, in our case the FCR market. Afterwards, in Section 3.2 we present the optimization method for arbitrage trading using energy and power capability profiles. In both sections, we provide examples using three EVs to show the functionality of the optimization methods.

3.1. Optimized combination of power capability profiles in balancing power markets

For optimization in balancing power markets, we use the weekly power capability profiles of the EVs introduced in Section 2.2. The goal of optimization is to maximize the revenues per EV contained in the pool. The optimizer consequently finds the optimal number of vehicles. Thereby, potential costs of the aggregation are ignored. Section 3.1.1 explains the optimization problem for the FCR market. In Section 3.1.2, we discuss the results of optimization. Afterwards, in Section 3.1.3, we present a linear optimization method with an assumed fixed number of EVs.

3.1.1. Optimization problem in balancing power markets

The optimization problem of adding EVs to a pool to maximize the revenue per EV contained in the pool is nonlinear with discrete decision variables. An EV x can be part of the pool (1) or not (0). Eq. (1) shows the optimization problem of finding the maximum FCR revenues per EV in the pool (Rev_{FCR}). The revenue depends on the decision variable $\vec{x}$, the price of FCR provision during each service period of a week ($\overrightarrow{price}_{FCR}$) and the EV power capability profiles consisting of the maximal possible charging ($\boldsymbol{P}_{ch}$) and discharging power ($\boldsymbol{P}_{dis}$). As weekly price curves, we use the average prices of each of the weekly 42 four-hour service periods of the second half of 2020 (see Section 2.1.1). The objective function Rev_{FCR} is calculated using Eq. (2). The decision variable $\vec{x}$ is a column vector that can contain the values 1 (in the pool) and 0 (not in the pool). The matrices $\boldsymbol{P}_{ch}$ and $\boldsymbol{P}_{dis}$ contain the EV power capability profiles in charge and discharge directions.

In the following, the individual parts of the objective function are described:

1) $\vec{a} = \min(\mathbf{P}_{ch} \bullet \vec{x}, \mathbf{P}_{dis} \bullet \vec{x})$ calculates the minimum of the charging and discharging power capability of the composed pool at any time depending on the decision variable $\vec{x}$. This is done because FCR must be provided simultaneously in both directions (Section 2.1.1). Thus, the minimum possible charging and discharging power determines the power that can be offered on the FCR market. $\vec{a}$ is then an m-dimension vector with the number of timesteps (m).
2) $b = \lfloor \min(a_{(i-1)\bullet 16+1,\cdots,i\bullet 16})/1.25 \rfloor$ takes the minimum value of the pool power in the specific service period i since only the minimal appearing power can be offered during the timeslot. A week has 42 4-hour service periods and each of these service periods contains 16 values corresponding to quarter hours. Furthermore, the value is divided by 1.25, since an additional 25% of the prequalified power must be kept available for storage management activities when offering FCR (see Section 2.1.1. Accordingly, only 80% of the minimum power can be used for FCR. Afterwards, the value is rounded down to multiples of 1 MW, since only multiples of 1 MW can be traded on the FCR market. If participating in the FCR market through aggregators, smaller units of power could also be marketed, but this is not assumed at this point.
3) The pool minimum of each time slot is then multiplied by the mean FCR price of the service period, and the resulting revenues are summed up for the weekly 42 service periods of four hours each.
4) This sum is then divided by the number of vehicles and multiplied by 52 weeks per year to estimate the revenue per year and vehicle.

$$\max\ Rev_{FCR}\left(\vec{x}, \overrightarrow{price}_{FCR}, \boldsymbol{P}_{ch}, \boldsymbol{P}_{dis}\right) \tag{1}$$

$$Rev_{FCR} = 52 \bullet \frac{\sum_{i=1}^{42} Price_{FCR}^{i} \bullet \left\lfloor \min\left(\left[min(\boldsymbol{P}_{ch} \bullet \vec{x}, \boldsymbol{P}_{dis} \bullet \vec{x}) \right]_{(i-1)\bullet 16+1,\cdots,i\bullet 16} \right) / 1.25 \right\rfloor}{\sum_{j=1}^{n} x_j} \tag{2}$$

With:

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad x_j \in \{0;1\} \ j = 1 \cdots n$$

$n: Number\ of\ Profiles$

$$\boldsymbol{P}_{ch} = \begin{bmatrix} p_{ch}{}_1^1 & p_{ch}{}_2^1 & \cdots & p_{ch}{}_n^1 \\ p_{ch}{}_1^2 & p_{ch}{}_2^2 & \cdots & p_{ch}{}_n^2 \\ \vdots & \vdots & \ddots & \vdots \\ p_{ch}{}_1^m & p_{ch}{}_2^m & \cdots & p_{ch}{}_n^m \end{bmatrix}$$

$$\boldsymbol{P}_{dis} = \begin{bmatrix} p_{dis}{}_1^1 & p_{dis}{}_2^1 & \cdots & p_{dis}{}_n^1 \\ p_{dis}{}_1^2 & p_{dis}{}_2^2 & \cdots & p_{dis}{}_n^2 \\ \vdots & \vdots & \ddots & \vdots \\ p_{dis}{}_1^m & p_{dis}{}_2^m & \cdots & p_{dis}{}_n^m \end{bmatrix}$$

$m: Number\ of\ Timesteps$

$$\overrightarrow{price}^{FCR} = \begin{bmatrix} price_1^{FCR} \\ price_2^{FCR} \\ \vdots \\ price_{42}^{FCR} \end{bmatrix}$$

To solve the described optimization problem, MATLAB's genetic

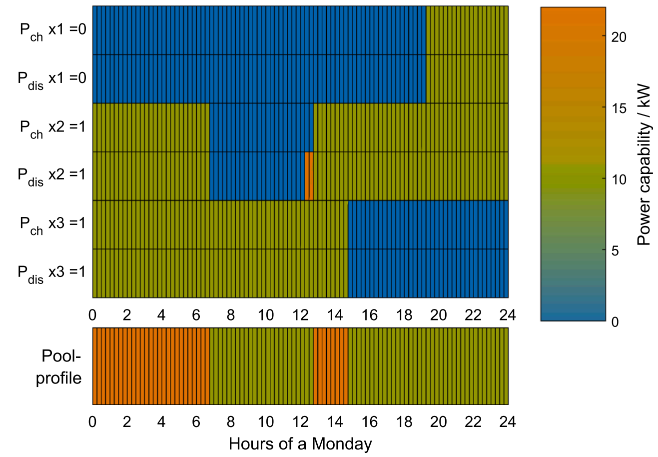

Fig. 3. Three power capability profiles (each in positive and negative directions) and their optimized pool profile for frequency containment reserve (FCR) provision.

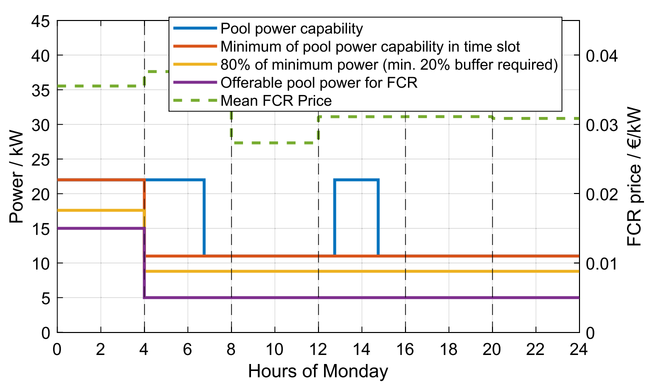

Fig. 4. Course of the pool's power capability profile, the minimum of the pool power capability in every service period and the offerable pool power for FCR for the pool of Fig. 3. Mean FCR price for the six time slots of Mondays between July 1st and December 31st 2020 from [57]. Minimum and increment: 5 kW; Revenue/EV/year: 241.5 €.

algorithm (GA) toolbox is applied [65,66]. Genetic algorithms are metaheuristic algorithms that use experience from nature to determine a feasible and well-suited solution by means of inheritance and crossing. Each new generation represents a further possible solution to the optimization problem. The optimization problems to be solved by genetic algorithms often have several local optima. For this reason, the algorithms use mutations during inheritance, so that the chance of finding a global maximum increases. Restarts at different positions also contribute to this goal. Due to their metaheuristics, genetic algorithms do not necessarily find the global optimum [66]. In 1996, genetic algorithms were already proposed in publications for metaheuristic optimization in different applications [67]. Since then, they have been further developed and are used, for example, for the optimization of hybrid generation systems consisting of photovoltaic, wind and storage systems [68,69].

The optimization problems presented in this paper are nonlinear. Adding or removing one vehicle can either increase or decrease the revenue per vehicle. MATLAB's GA can approximately solve this nonlinear optimization problem with discrete decision variables [65]. Since each of the 468 vehicles used has two possibilities (0 or 1), there are $2^{468} \approx 7.6 \bullet 10^{140}$ possible pool compositions. This number of combinations can no longer be checked manually. For this reason, in the next section the optimization is performed in a simplified way as an example with three power capability profiles for one day.

3.1.2. *Results of optimization using three profiles*

In this section, exemplary power capability profiles of three EVs are used (x1, x2, x3) and the pool's revenue per EV is maximized using the presented algorithm. As a condition, it was demanded here that at least 5 kW must be provided. Furthermore, increments of 5 kW are possible. For the provision of FCR, this condition will be set to 1000 kW with increments of 1000 kW. In addition, only one day is considered (Monday) at this point. The mean FCR prices for the six service periods of Mondays are used in this exemplary optimization.

In Fig. 3, the absolute values of three exemplary power capability profiles x1, x2 and x3 are depicted in positive and negative directions. EV x1 can provide 11 kW in positive and negative directions from approximately 7p.m. until midnight. EV x2 can provide 11 kW the whole day except for a time section between 6:45 a.m. and 12:45p.m. Moreover, EV x2 could provide positive power of 22 kW between 12:15p.m. and 12:45p.m. by stopping the charging process and discharging its battery instead. During those 30 min, the EV cannot provide negative power since the EV is already charging with its maximum power of 11 kW. EV x3 can provide positive and negative power of 11 kW from midnight to 2:45p.m.

The optimizer chooses the profiles x2 and x3 to be in the pool. Using those two maximizes the revenue per EV. Adding profile x1 to the pool would increase the available pool power in the service period from 8p.m. to midnight. However, the additional pool revenue would not be high enough to increase the revenue per EV, since the pool revenues had to be divided among three EV owners. For this reason, EV x1 is not used in the pool. Furthermore, the resulting pool profile shows that only the minimum amount of positive and negative power is used. Since EV x2 can provide 22 kW of positive power between 12:15p.m. and 12:45p.m., the pool would be able to offer 33 kW of positive power. However, since the negative pool power is 11 kW, the possible FCR pool power is 11 kW during those 30 min.

Fig. 4 shows the available pool power capability during Monday (blue line) and the minimum pool power in each 4-hour service period (red line). Due to the buffer of at least one fourth of the FCR power, another 20% is subtracted from this minimum (yellow line). Moreover, the figure contains the offerable pool power when providing balancing power with the described condition of a minimum and an increment of 5 kW (purple line). The pool can provide 15 kW during the first time slot and 5 kW during all others. Using the FCR prices displayed in Fig. 4 the yearly revenue per EV can be estimated. Since we made simplifications in this example, the annual revenues are not realistic in practice.

To demonstrate that the optimization method work correctly, the revenues per vehicle and year were calculated manually for all combinations of the three profiles (see Appendix Fig. A1). The diagram shows that the combination of profiles x2 and x3 leads to the highest revenue per EV.

3.1.3. *Linear optimization with fixed number of vehicles*

Another approach than finding the optimal number of EVs would be to specify an exact number of vehicles to be selected optimally. The genetic algorithm could receive a fixed number in a constraint. However, the metaheuristic optimization of the FCR market showed that the algorithm cannot guarantee to find the global optimum and might become stuck in a local optimum. For this reason, we created a linear optimization algorithm that uses a fixed number of vehicles as a constraint. We specified to this optimizer that it should select the best 100 EVs out of all possible EVs, for example, and maximize the revenue per vehicle.

The mixed-integer linear problem has two integer decision variables. First, the offered power that is provided from the EV pool ($\overrightarrow{P}^{FCR}$). Second, a binary variable ($\overrightarrow{x}$) that determines if a specific power capability profile is selected in the optimized vehicle pool. Depending on the defined input parameter of the number of vehicles in the optimized pool (N), the decision variables are optimized in the objective function (3)

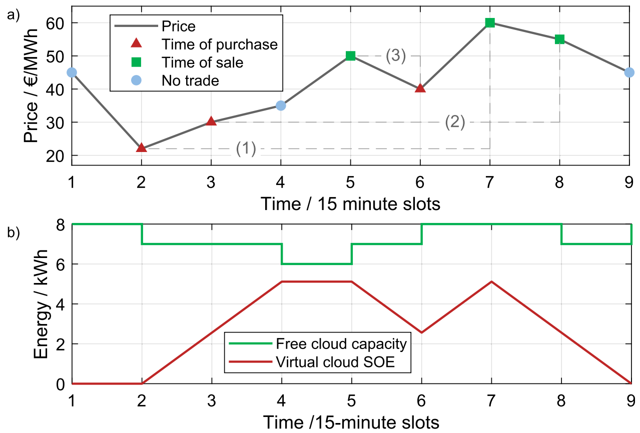

Fig. 5. Working principle of the arbitrage algorithm. a) Exemplary price curve and trading activity. b) Free cloud capacity and virtual cloud SOE curve.

and two constraints.

$$\max \sum_{i=1}^{42} P_i^{FCR} \bullet price_i^{FCR} \quad (3)$$

$$\overrightarrow{P}^{FCR} = \begin{bmatrix} P_1^{FCR} \\ P_2^{FCR} \\ \vdots \\ P_{42}^{FCR} \end{bmatrix}$$

The first constraint (4), determines that FCR power is provided in the respective 1 MW increments and that the reserve power of 25% is added when participating in the market. Since the FCR is a symmetrical product that must be provided in both positive and negative directions, the lesser of the charging and discharging power indicates the power offered.

Eq. (5) guarantees that the sum of activated EVs in the optimized vehicle fleet corresponds exactly to the defined input parameter. The sum over all participating EVs (Eq. (5)) corresponds to the denominator in the genetic algorithm (Eq. (2)). In the genetic algorithm, we divided by the sum to optimize the revenue per vehicle over all possible quantities.

$$\overrightarrow{P}^{FCR} \bullet 1MW \bullet 1.25 \leq \sum \overrightarrow{x} \bullet min(P_{\mathrm{ch}}, P_{\mathrm{dis}}) \quad (4)$$

$$\sum_{j=1}^{n} x_j = N \quad (5)$$

The optimizers presented in this section are applied to the 468 power capability profiles in the FCR market and the results are presented in Section 4.1.

3.2. Optimization of the combination of power and energy capability profiles for arbitrage in spot markets

In this section, the optimizer for arbitrage trading on the intraday continuous and day-ahead auction market is presented. As before, we maximize the revenue per participating EV. Section 3.2.1 shows the optimization problem and explains the algorithm. Afterwards, Section 3.2.2 shows an example of arbitrage trading using three vehicles.

3.2.1. Optimization problem for arbitrage in spot markets

Arbitrage trading differs from smart charging, which is often used in the literature. In smart charging, purchases on the spot market are optimized for charging vehicles at times of low electricity costs. The arbitrage trading presented here, in contrast, is based on a free cloud capacity. This free cloud capacity is the sum of the free capacities of all vehicles in the pool. Moreover, we calculate a virtual cloud SOE, which represents the virtual state of energy of the pool. By using only the free capacities, the primary use of the EVs is not limited. In the following, the optimization process and the algorithm for the calculation of arbitrage revenue are explained.

In principle, this optimization maximizes the revenue per participating EV. For this purpose, we use another genetic optimization algorithm that varies the composition of the pool, calls the arbitrage algorithm, and receives the revenues per participating EV. Here, taxes and fees payable by households when purchasing electricity are excluded, similar to [70]. At the beginning, we define three characteristic values: The minimum price spread in €/MWh, the one-way efficiency of charging and discharging respectively, and the minimum bid size to trade on the intraday continuous or day-ahead auction market. The minimum price spread is set at 10 €/MWh, since this significantly reduces the number of cycles that the batteries make, while barely reducing revenues [70]. As one-way efficiency, we assume 93 % in both directions based on measurements [10]. In addition, 100 kW is used as the minimum offer size and increment analogous to the EPEX Spot markets. For hourly day-ahead auction trading, this means trading in 100 kWh increments. For 15-minute intraday continuous trading, 25 kWh increments are traded. A trade will not be executed below the minimum price spread and the minimum bid size.

The arbitrage algorithm then receives the following input data:

- The three characteristic values defined beforehand (minimum price spread, efficiency, minimum bid size).
- Average 15-minute-prices of the EPEX intraday continuous market from 2020 or the 1-hour-prices of the EPEX day-ahead auction market from 2020, respectively.
- Aggregated free cloud capacity of the current composite pool in kWh for every time slot of 15 min or 1 hour, respectively.
- Power capability profile of each participating EV including distinction between grid-sided and battery-sided power weighted with the efficiency.

Since bidding strategies are not a focus of this paper, average prices for the two markets under consideration are used. The algorithm thus calculates the possible revenues on this basis and does not try to beat these average prices through bidding procedures. In general, the algorithm identifies purchase times of low prices and assigns them to high price sale times. An exemplary price development and the SOE curve resulting from arbitrage trading are shown in Fig. 5. First, the price minimum of the period under consideration is determined and is marked as the first time of purchase (Time 2). Afterwards, a possible time of sale is iteratively searched for starting with the time of highest price (Time 7). The trade is executed when:

a) the virtual cloud SOE remains between zero and the maximum free cloud capacity,
b) the trade exceeds the minimum price spread and the minimum offer.

If these conditions cannot be met, this potential sale time is temporarily excluded and the time of the next highest price is tested as a sale time. This method is executed iteratively until a suitable sale time has been determined. The purchase and sale times are blocked for further iterations and the temporarily excluded purchase times are released again.

A purchase at time 2 and a sale at time 7 is possible, so that combination (1) from Fig. 5 can be executed. The combination is marked by the dashed line. Next, time 8 is selected as time of sale and time 3 as time of purchase. This combination also does not violate any conditions and is therefore executed as combination (2). Subsequently, time 5 is identified as the next time of sale. The next lowest purchase price is at time 4, but since this trading would exceed the maximum virtual capacity, this time

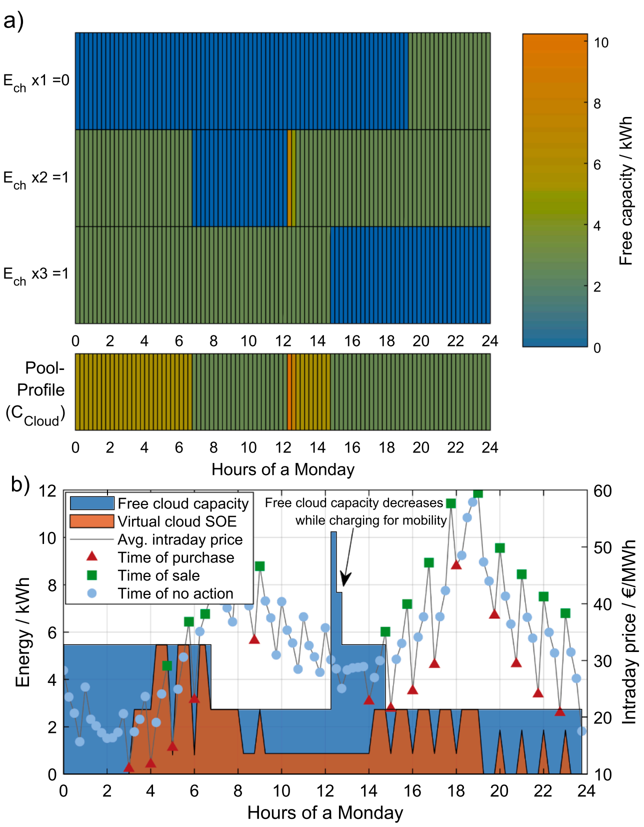

Fig. 6. a) Negative energy capabilities of three EVs in 15-minute resolution over a Monday and pool profile (free cloud capacity) in 15-minute resolution. b): Free cloud capacity and virtual cloud state-of-energy (SOE) with average intraday continuous price curve and marked prices of purchase and sale.

of purchase cannot be realized. Instead, since the virtual battery already contains energy before the sale, times of purchase after the time of sale are also permitted. Within this search, time 6 is identified as the time of purchase and time 5 is set as the time of sale (see combination (3)). A sale time that lies before its assigned purchase time retroactively changes the physical assignment of purchase and sale times, but this has no effect on the accounting. The resulting revenue is then calculated according to Eq. (6), considering the losses that occur during charging and discharging.

$$Rev_{Arbitrage} = \sum_{n=1}^{\#trades} (Price\ sale_n - Price\ purchase_n) \bullet P_n \bullet \Delta T \bullet \eta_{round-trip} \tag{6}$$

The optimizer then receives the resulting revenues of the current pool composition. Then, the algorithm is started with a different pool composition and its revenues are calculated. As in FCR optimization, this genetic optimization uses inheritance and mutation to change the pool composition in order to determine the optimal pool composition (see Section 3.1).

3.2.2. *Results of optimization using three profiles*

Similar to the FCR optimization, the spot market optimization is now presented with three exemplary profiles (x1, x2, and x3). In this example, the intraday continuous market with its 15-minutes resolution is used. The explanations are also valid for the day-ahead auction market with its 1-hour resolution. Furthermore, in this example we only consider Monday instead of the whole week, analogous to the FCR example. In addition, only this example defines 1 kWh as the minimum bid size, since the three vehicles cannot reach a bid size of 25 kWh required by the EPEX. However, the efficiency and the price spread are assumed to be 93 % and 10 €/MWh respectively, as described above.

Fig. 6 a) shows the negative energy capability profiles (energy that can be charged) of the exemplary vehicles x1, x2 and x3 in 15-minute resolution during Monday. EV x1 is on the road until 7p.m. and can store 2.7 kWh after arrival. EV x2 is on the road between approx. 7 a.m. and 12:30p.m. and can also store 2.7 kWh during the parking time. In addition, it can store up to 7.5 kWh for a short time after arrival at 12:30p.m., since the vehicle battery then has a lower SOE due to the journey just completed. Vehicle x3 is connected until 2p.m. and can store 2.7 kWh of energy at any time. The optimizer selects EV x2 and x3 for the pool so that the free cloud capacity shown corresponds to the sum of the free capacities of EV x2 and EV x3.

In Fig. 6 (b), the free cloud capacity and the virtual cloud SOE are shown. Moreover, the average Monday intraday continuous price curve is displayed (right y-axis). Purchase times are marked with a red triangle and sale times with a green square. The arbitrage algorithm determines 14 trades on Monday with the pool consisting of EV x2 and EV x3. At the times of purchase, most often 2.75 kWh are purchased on the grid side, of which 2.56 kWh are stored due to efficiency. At the times of sale, 2.38 kWh are then delivered to the grid. The revenue is finally calculated according to Eq. (6) over one year at 86.2 €. The results of the manual calculation of the intraday continuous revenue of the various combinations of x1, x2 and x3 are shown in Fig. A2. Analogous to the FCR optimization, the optimizer found the combination with the highest revenue per participating EV.

4. Results

This chapter shows the results of the optimization of the various pool compositions. Section 4.1 analyzes the weekly profiles of the optimized pools. In addition, the revenues of the optimized pools are compared with the revenues of randomly assembled pools of the same number of vehicles. Section 4.2 examines the additional degradation of EV batteries in dual use. Here, an example is used to simulate battery degradation during uncontrolled charging, primary use-oriented charging and dual use-oriented charging.

4.1. *Comparison between optimized and random pools*

First, the optimized pools are compared to randomly assembled EV pools. For this purpose, the optimization problems presented in chapter 3 are solved. The results are optimized pool compositions that provide maximum revenue per participating EV. In the following, the results for the provision of FCR and arbitrage trading on the intraday continuous and day-ahead auction market are presented. This is followed by an economic comparison of all markets.

4.1.1. *FCR market comparison*

First, the results of the optimization of pool composition in the FCR market are explained. Fig. 7 shows the accumulated weekly pool profile of one random EV pool (a) and the optimized pool (b) when providing FCR. The corresponding assumptions and the results of the optimization are presented numerically in Table 4. The achievable prices are derived from the mean values of the 42 weekly 4 h-slots of the months July to December in the year 2020. In addition, as usual in the FCR market, 1 MW was assumed as the offerable minimum power increment. The power capability profiles introduced in Section 2.2 were used for the FCR optimization.

If the annual revenue per vehicle is maximized, the optimization method selects 243 EVs, resulting in a total revenue of about 92,000€. Per participating EV, 378 € can be generated yearly. If FCR were provided 10,000 times using a random pool of 243 EVs, the total yearly revenue would on average be 53,400 €, which results in 220 € per vehicle. In this case, the standard deviation of revenue per vehicle is 9.5 €.

The power values displayed in Fig. 7 show the minimum power capability in both directions at any time, since positive and negative FCR

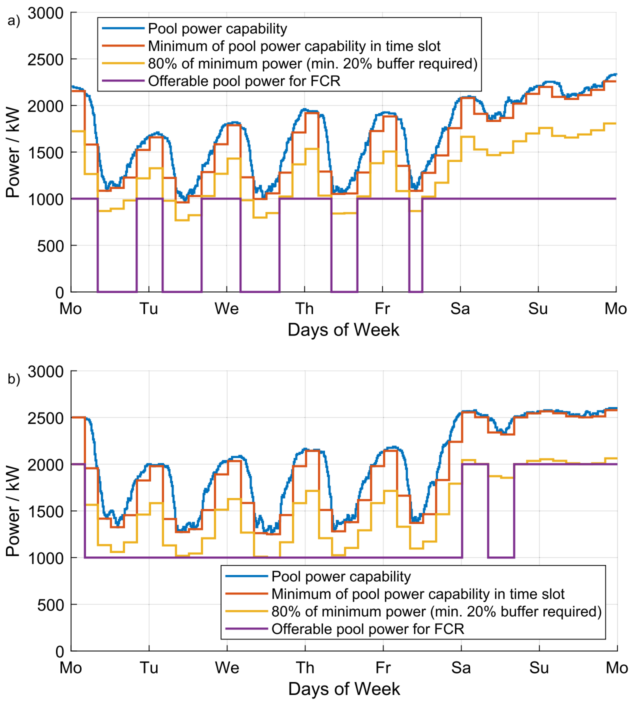

Fig. 7. Weekly pool profiles of one random pool of 243 EVs (a) and the optimized pool of 243 EVs (b) when providing frequency containment reserve (FCR). Since at least an additional 25% of the offered FCR power must be provided as buffer, 20% of the minimum pool power capability is blocked (see Section 2.1.1).

Table 4
Assumptions and results of FCR pool optimization.

Parameter	Value/ Data	
FCR prices	Average prices of 4 h-slots between July and September 2020	
Minimum bid and increment	1000 kW	
Parameter	**Optimized pool**	**Mean of 10,000 random pools**
Number of EVs	243	
Power utilization rate (τ_{PUR})	62.2 %	39.3 %
Annual Pool Revenue	91,854 €	53,367 €
Annual Revenue per EV	378 €	220 €

must be supplied simultaneously (see 2.1.1). The randomly assembled pool can offer a maximum of 1 MW. Particularly during daytimes on weekdays the power that can be offered drops below 1 MW due to the required buffer of 25% of the offered power. If the composition of the pool is optimized, the pool can provide 1–2 MW to the FCR market. The pool can use its available power more efficiently, generating higher revenues per EV. During the weekdays, the pool offers 1 MW, although the pool could often offer 1.5 MW at night. On weekends, the optimized pool can offer 2 MW apart from Saturday noon. Comparing the random pool's available power and the optimized pool's power, it can be seen that the optimizer only includes the minimum required number of EVs in the pool to provide the 1 MW or 2 MW, respectively.

A parameter introduced at this point is the power utilization rate (τ_{PUR}). This value describes quantitatively how much of the possible usable power is actually used for FCR provision. For this purpose, the difference between the available power (power capability) and the offerable FCR power is calculated and scaled to the power capability (Eq. (7)). The average value is then calculated over the 672 15-minute time periods of the week and subtracted from one. Graphically, the parameter represents the mean percentage gap between the blue and purple curves from Fig. 7. At a value of one, the curves lie on top of each other, and the entire power is used. At a value of zero, none of the possible power is used. Due to the required buffer of 25% of the FCR power (i.e., min. 20% of the power capability), the maximum achievable τ_{PUR} is 80%.

$$\tau_{PUR} = 1 - \frac{1}{672}\sum_{t=1}^{672}\frac{power\ capability(t) - FCR\ power(t)}{power\ capability(t)} \tag{7}$$

The values of τ_{PUR} for pool compositions of 10,000 random pools and the optimized pool are displayed in Table 4. While the random pools on average reach a τ_{PUR} of 39%, the optimized pool improves the τ_{PUR} to 62%. Consequently, the optimal pool makes better use of its potential and increases its efficiency (see Fig. 7). Thus, the usage of the V2G potential in the FCR case is increased though the optimized pool combination by almost 60%.

Since the optimizer determined the optimal number of vehicles at 243 EVs and we compared the result with a random pool of 243 EVs, in the following, the pool is composed of a fixed number of EVs. For this purpose, the linear optimization method presented in Section 3.1.3 is used. We chose a fixed number of 50 to 450 vehicles with equidistant distances of 50 vehicles to cover the spectrum between very few EVs and the maximum number of 468 possible EVs. After the optimization, 10,000 random pools with the respective fixed number were composed and the revenue per EV was determined. The results of the optimization with a variable number of EVs (orange dot), the optimization with a fixed number of EVs (blue dot) and random pools (boxplots) are depicted in Fig. 8. It turns out that an amount of 50 or 100 EVs is not sufficient to provide FCR power. From 115 EVs on, FCR can be offered in the optimal case. Random EV pools can increase their revenue per vehicle as the number of vehicles increases. This is because they can better serve the increments of 1 MW when increasing their number. Due to these increments, the revenue per vehicle is also not linear but drops briefly between 150 and 250 vehicles for the optimized pools, for example. Revenue per vehicle also appears to converge as the number increases, changing little between 350 and 450 vehicles. However, this is because 468 vehicles were considered in this analysis. If, for example, 1,000 different EVs were considered, revenues would probably not converge between 350 and 450. The optimizer achieves an increase in revenue per EV in each case. However, its advantage decreases as the number of EVs increases. Again, the small advantage of the optimizer at 450 vehicles exists because we considered 468 vehicles in total.

As shown with the genetic algorithm, the optimizer found the optimal number of EVs to maximize revenue per EV at 243 vehicles. Especially at a fixed 150 EVs, the advantage of the optimizer becomes apparent: While the random pools reach an average of 109 €/EV and a maximum of 160 €/EV, the optimizer can generate 370 €/EV. The increase in revenue corresponds to a factor of 2.3 compared to the best random case and 3.4 compared to the average of the random pools.

4.1.2. Intraday continuous market comparison

In addition to providing balancing power, EV energy can also be traded on the spot market. The optimization of arbitrage trading on the intraday continuous market that was used here was explained in Section 3.2. Executing this optimization results in an optimized pool of 48 vehicles, whose free cloud capacity and virtual cloud SOE are shown in Fig. 9 (a). By using the widest possible price spreads, areas are created where the free capacity of the vehicle batteries is not used, such as Saturday and Sunday mornings. Diagram b) of Fig. 9 shows the weekly mean weighted average price curve of the 15-minute intraday continuous prices. In addition, buy and sell times are color-coded. Thereby the algorithm uses the spread limit of 10 €/MWh shown in Table 5. Possible transactions below this threshold are not executed. Furthermore, Table 5 numerically shows the assumptions and results of intraday optimization. If the revenues per participating EV are optimized in the intraday continuous market, the optimization method selects 48 of the 468 possible EVs. These generate annual profits of 9,748 €, which corresponds to 203 € per participating EV. If the aggregator adds 48 random

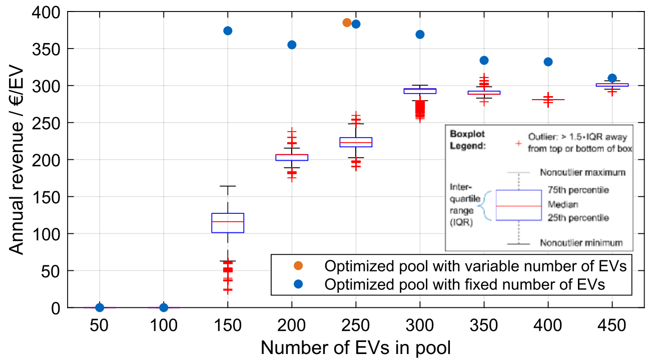

Fig. 8. FCR optimization: Annual revenue per EV when a fixed number of EVs are specified (boxplot: 10,000 random pools, dots: optimized pools).

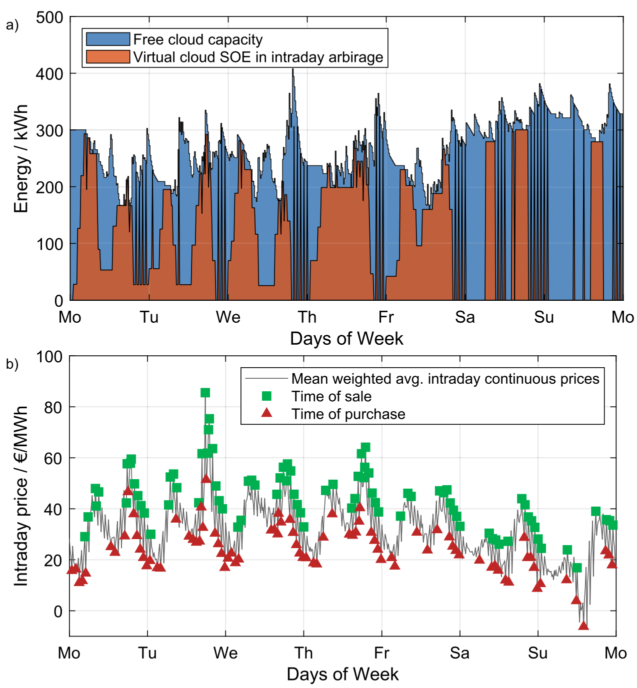

Fig. 9. Intraday continuous optimization: Free cloud capacity and virtual cloud SOE of the pool (a) and times of sale and purchase including intraday continuous prices (b).

vehicles to the pool, the total annual revenue would be 3,649 € on average, which corresponds to 76 € per participating EV (standard deviation of 8.1 €/EV).

Analogous to the FCR case, optimization including finding the optimal number was followed by optimization for a fixed number of EVs. In contrast to the FCR case, the number was given to the genetic algorithm as a constraint instead of developing a linear optimizer due to the complexity of the function. The results of the optimized (points) and the random pools (boxplots) are depicted in the same way as in the FCR case in Fig. 10.

The intraday case shows that as few as 50 vehicles can already provide arbitrage trading. Furthermore, the revenues per EV are relatively constant for random pools over all analyzed vehicle numbers between 48 € and 103 €. The optimal number of 48 EVs achieves revenues of 203 € per vehicle (orange dot). With an increasing number of vehicles, the advantage of the optimizer decreases again. For example, with 150 vehicles, the optimizer achieves annual revenues of 118 € per EV, while the random pools can only generate 77 € on average.

Table 5
Assumptions and results of intraday continuous arbitrage pool optimization.

Parameter	Value/ Data	
Intraday continuous prices	Weighted average prices of 15-minute slots on weekly basis of the year 2020	
Minimum bid and increment	0.1 MW	
Assumed efficiency	93 % one-way (86.49 % round-trip)	
Spread limit	10 €/MWh	
Parameter	**Optimized pool**	**Mean of 10,000 random pools**
Number of EVs	48	
Energybought and sold	784 MWh678 MWh	283 MWh244 MWh
Avg. Price of Energy bought and sold	21.77 €/MWh39.55 €/MWh	21.92 €/MWh40.28 €/MWh
Annual Pool Revenue	9,748 €	3,649 €
Annual Revenues per EV	203.1 €	75.9 €

4.1.3. Day-ahead auction market comparison

Arbitrage trading can also take place on the day-ahead auction market. If optimization is executed for the day-ahead market, the optimization method selects 61 EVs that maximize the revenue per EV. The resulting free cloud capacity is shown over the course of the week together with the virtual cloud SOE in Fig. 11 (a). The lower diagram shows the weekly course of the average day-ahead auction prices together with color-coded buy and sell times. Table 6 shows the numerical assumptions and results. In general, the assumptions in the day-ahead optimization were the same as in the intraday optimization. Instead of the quarter-hourly intraday continuous prices, the hourly day-ahead auction prices were assumed as the average weekly price curve. In the day-ahead arbitrage optimization, the profiles introduced in Section 2.2 were used.

In the day-ahead auction market, annual revenues for the 10,000 random pools of 61 EVs amount on average to 11 €, which is about 0.17 € per EV. The very low average revenues are because a random pool of 61 EVs often cannot do any arbitrage trading at all on the day-ahead market due to the delivery time of 1 h. Out of the 10,000 random pools, 9,413 could not generate any arbitrage revenue on the day-ahead market. The average revenue of the pools that could generate any revenue at all was 3.50 €/EV.

The selected 61 EVs of the optimizer reach around 1,700 €, which is about 28 € per EV. Due to the longer provision time of the day-ahead auction market, the arbitrage algorithm can trade far less in this market compared to the intraday continuous market and exploit fewer price spreads (Fig. 11).

Analogous to the intraday case, we analyze fixed numbers of vehicles in the following. The results of the optimization with a fixed number are depicted in Fig. 12. In contrast to the intraday continuous market, 50 EVs are not sufficient for arbitrage trading on the day-ahead market due to the longer delivery time. However, the optimal number of EVs selected from the pool is 61 as the orange dot in Fig. 12 shows. As the number increases, the revenue per vehicle converges to about 13 € per vehicle. The optimizer again has the greatest advantage with small pools. Here it can select the best EVs and, for example, reaches 20 € per EV with 150A vehicles. In contrast, 10,000 random pools of 150 vehicles generate on average only 11.74 € per vehicle. Consequently, the advantage of the optimizer over random pool compositions is again evident in this case.

4.1.4. Comparison between the markets

Following individual considerations of the optimized pools of the three markets, the potential revenues between the markets are now compared. The increase in annual revenue per EV through optimization in the three markets is shown in Fig. 13. The revenue from participation in the FCR market can be increased by 72 % from 220 € to 378 € through optimized pool composition. The earnings from intraday continuous arbitrage trading can be increased by 167 % from 76 € to 203 €. On the

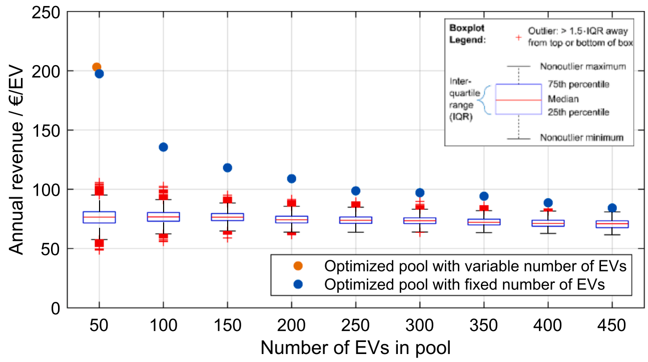

Fig. 10. Intraday continuous optimization: Annual revenue per EV when a fixed number of EVs is specified (boxplot: 10,000 random pools, blue dot: optimized pool). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

day-ahead market, optimization of the pool can yield 28 € per EV instead of an average of 3.5 € when only considering random pools of 61 EVs that actually generate any revenue. This is an increase in revenue by almost 7-fold.

A comparison of the possible markets shows that participation in the FCR market could generate significantly higher revenues than arbitrage trading in 2020. Without optimization, it is most economical in all cases to include as many EVs as possible in the pool, since revenue per EV increases as the number of vehicles increases with random pool composition (see Fig. 8, Fig. 10 and Fig. 12). With optimization, the revenue on the FCR market is 1.9 (vs. intraday) and 13.5 times (vs. day-ahead) higher than the income that can be generated by arbitrage trading.

With respect to pool sizes, however, it is important to note that small vehicle pools of <100 EVs do not meet the 1 MW minimum for FCR (see Fig. 8). Pools of this size that have already been assembled could

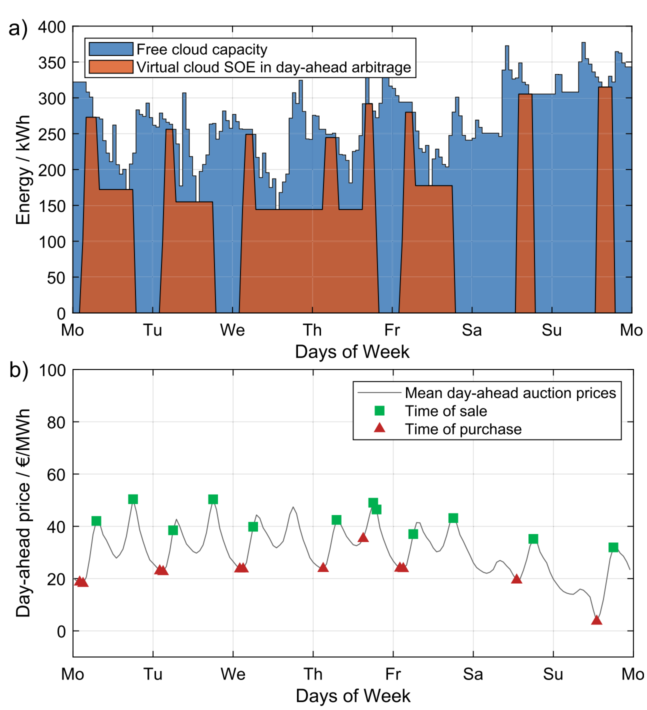

Fig. 11. Day-ahead optimization: Free cloud capacity and virtual cloud SOE of the pool (a) and times of sale and purchase including day-ahead auction prices (b).

consequently provide arbitrage trading, whereby the intraday continuous market is more flexible and promises higher revenues compared to the day-ahead auction market.

Overall, these analyses demonstrate that the optimal pool composition using the capability profiles can substantially increase the revenues an aggregator can generate in the markets. Thus, the optimized profile combination is relevant for an aggregator to achieve competitive advantages.

4.2. What is the influence of dual use on battery degradation?

For an estimation of battery degradation costs, the degradation of a vehicle battery in "normal" operation and in dual use operation is compared in the following. The log data of vehicles used in this work, from which the power capability profiles were determined, do not include power profiles for the trips (see Section 2.2). Thus, the estimation of the charged and discharged power during a trip is based on the data measured by Bremer et al. [71]. This vehicle is part of a geriatric care fleet that runs two shifts daily (approximately 6 a.m. to 2p.m. and 3p.m. to 10:30p.m.). The vehicle model is a Smart fortwo electric drive with an energy capacity of 18 kWh [71]. For the following analysis, we assumed the vehicle with this driving profile would have been part of each pool. To do this, five daily power profiles and corresponding state-of-charge (SOC) profiles were formed (Fig. 14 and Appendix Figs. A3-A7), representing the following five cases:

- Uncontrolled charging (UC)
- Primary use-oriented charging (PUC)
- Dual use-oriented charging for FCR provision (DUC-FCR)
- Dual use-oriented charging for intraday continuous arbitrage (DUC-ID)
- Dual use-oriented charging for day-ahead auction arbitrage (DUC-DA)

With UC, the EV battery is immediately recharged to a SOC of 100 % upon arrival at the company site, i.e., at the end of the shifts (Fig. A3). Between shifts, the SOC is kept constant at 100 %. The PUC strategy, however, charges only enough to fulfill the mobility needs (Fig. A4). For this purpose, we defined a reserved capacity for the mobility as a function of time. The reserved capacity defines the minimum SOC at any time during the day. Since shifts occur between 6 a.m. and 10:30p.m., a minimum SOC of 60 % was defined for these times. Outside of these times, the minimum SOC is 30 %. This way, there is enough energy in the vehicle battery for spontaneous trips and the required energy is available for typical shifts. This type of charging corresponds to a smart charging strategy, since high SOCs over longer periods of time lead to accelerated degradation of the battery [20,72,73].

In the three dual use strategies, the EV provides FCR (DUC-FCR) or trades on the intraday continuous (DUC-ID) or day-ahead auction market (DUC-DA). A default SOC of 68% was chosen to form the respective SOC curves (Figs. A5-A7). This SOC allows cycling for the second use during parking times without restricting mobility. For the simulation of FCR provision when the EV is parked at the company's site, a standard battery energy storage load profile in FCR operation was used (Fig. A5) [74]. For the simulation of intraday continuous and day-ahead trading, Wednesday trading from Section 4.1 was used and scaled to one vehicle, i.e., divided by the number of vehicles in the optimized pool (Figs. A6-A7).

Since the vehicle under consideration is used as a geriatric care EV, it is assumed for this estimation of EV battery degradation that the SOC profiles are repeated 365 times per year and over several years. In reality, the driving profile and FCR generation or electricity trading will vary over the days and years. These profiles are then simulated with the

Table 6
Assumptions and results of day-ahead auction arbitrage pool optimization.

Parameter	Value/ Data	
Day-ahead auction prices	Average hourly day-ahead auction prices of the year 2020	
Minimum bid	0.1 MW	
Assumed efficiency	93 % one-way (86.49 % round-trip)	
Spread limit	10 €/MWh	
Parameter	**Optimized pool**	**Mean of 10,000 random pools**
Number of EVs		61
Energy bought and sold	108 MWh 93 MWh	0.57 MWh 0.49 MWh
Avg. Price of Energy bought and sold	19.77 €/MWh 41.13 €/MWh	11.70 €/MWh 35.03 €/MWh
Annual Pool Revenue	1,702 €	10.66 €
Annual Revenues per EV	27.91 €	0.17 €

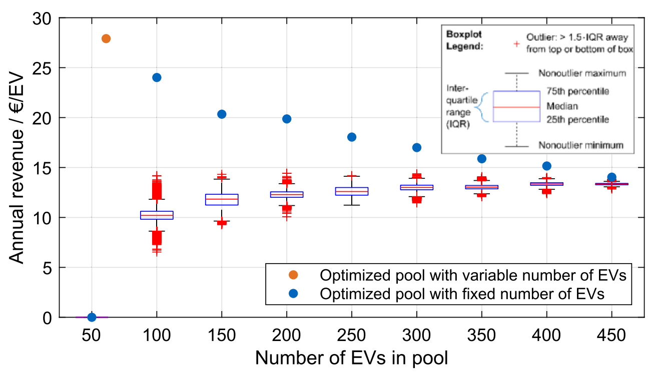

Fig. 12. Day-ahead optimization: Annual revenue per EV when a fixed number of EVs is specified (boxplot: 10,000 random pools, dots: optimized pools).

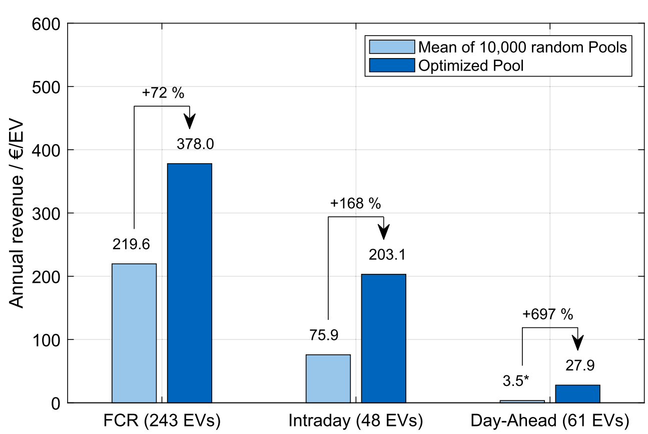

Fig. 13. Comparison of revenues in the three markets between the 10,000 random pools and the optimized pool (* Mean for random day-ahead pools of 61 EVs that could generate any revenue; 94% of the 10,000 pools could not generate any revenue).

storage simulation tool SimSES[2] (Simulation of stationary energy storage systems) to determine the degradation [75,76]. Here, a 1-minute resolution was chosen to allow an optimum between accuracy and computational time. In the simulation, parameters such as the capacity of 18 kWh are defined and the specified SOC curve is traced. For this purpose, a lithium-ion battery technology NMC (Nickel-Manganese-

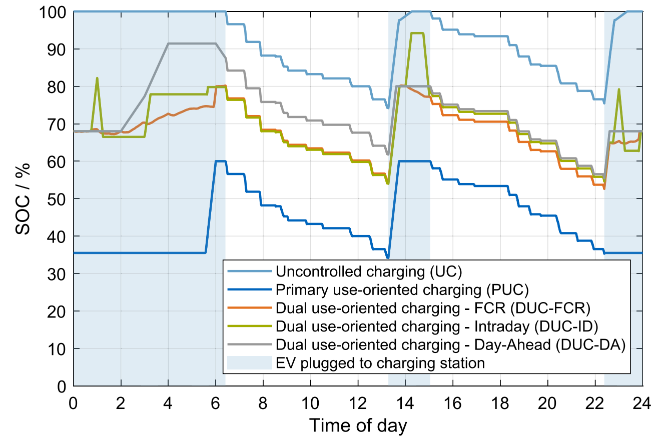

Fig. 14. Daily SOC-Profiles of the five considered cases.

Cobalt) was assumed to be the vehicle battery. The battery and degradation model of this cell type are based on a publication from Schmalstieg et al. [72]. The assumed fixed ambient temperature was 15 °C. Since vehicles might be parked in garages, this value is above the average temperature of 10.6 °C in Germany in 2020 [77]. A remaining capacity of 80% was selected as the end of life (EOL) of the battery in the simulations, analogous to the literature [72].

The results of the five simulations are shown in Table 7 and Fig. 15 (a). The case of uncontrolled charging (UC) leads to an average SOC of over 90% and a battery lifetime of about 7.7 years. In contrast, for the PUC case with an average SOC of 44.4%, the vehicle battery reaches its end of life after 12.8 years. This shows the advantage of a smart charging strategy, which in this simulation and with this profile leads to an increase in lifetime of 66%. The dual use with the EV leads to a mean SOC between 67% and 74% and a lifetime between 7.4 and 11.8 years, depending on the case. In this example, dual use in FCR and day-ahead case is better than uncontrolled charging (UC) in terms of battery aging, but worse than smart charging (PUC). Only intraday continuous arbitrage trading leads to a slightly lower lifetime than UC. The average annual equivalent full cycles (EFC) that the vehicle battery experiences without dual use are already relatively large at 160 due to the use of the vehicle in two shifts. With dual use, the annual EFCs increase up to 317 for intraday continuous arbitrage. In contrast, the EFCs for FCR provision and day-ahead trading are only slightly higher than the EFCs without dual use. This is because the exemplary supply or exemplary trading is very much in the EV's favor. In Fig. 14, it can be seen that the provision of FCR between 2 a.m. and 6 a.m. results in less need to charge the vehicle. The same applies to day-ahead trading between 2 a.m. and 4 a.m. By assuming that this day is repeated 365 times per year for several years, this results in only slightly more battery degradation of DUC-FCR and DUC-DA compared to PUC.

Table 7 additionally shows a utilization ratio. This ratio indicates the proportion of time the EV is on the road (not at company site) or in V2G provision. The value therefore indicates how often the vehicle battery is used. Dual use increases this utilization ratio: For example, almost 70% for intraday trading and 100% for FCR provision, since the vehicle provides FCR or is recharged as soon as it is parked at the company site. In addition, the dual use ratio shows the proportion of time the EV is parked at the company location that is used for FCR provision or trading.

After the example aging simulation, the costs for the battery are now compared with the possible revenues in the three markets considered (Fig. 15 (b)). According to a study, the average lithium-ion battery pack prices in 2020 were 137 \$/kWh, which is roughly equivalent to 114 €/kWh [78]. A vehicle battery pack with a capacity of 18 kWh therefore cost 2,052 € in 2020. If these costs are evenly distributed over the number of lifetime years, the battery costs without dual use range between 160 € (PUC) and 276 € (UC) for the example year 2020. The

[2] http://www.simses.org, open-source version 1.0.4

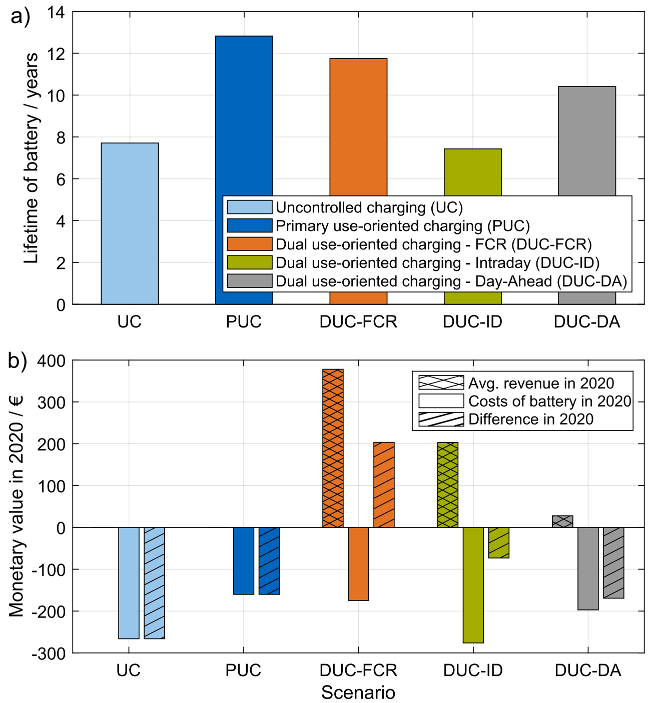

Fig. 15. Comparison of lifetime (a) and costs of battery and avg. revenues (b) for the five cases.

battery costs in dual use range between 175 € (DUC-FCR) and 276 € (DUC-ID). In Fig. 15 (b), the costs are plotted negatively. The average revenues per EV of the optimized pools in 2020 for the dual use cases are shown as positive values. Here, it can be seen that the revenues exceed the battery costs in the case of FCR supply. For intraday and day-ahead arbitrage, the battery costs are higher than the potential revenues. In the UC and PUC cases, no revenue is generated.

The comparison of the cases shows that, in regard to battery costs and revenues, all cases are better than the UC case. In the DUC-DA case, the difference between revenues and battery costs is slightly less than the difference in the PUC case due to low revenues in the day-ahead auction market. Smart charging according to PUC therefore seems to be more profitable than arbitrage trading on the day-ahead auction market. However, for intraday trading and especially for FCR provision, the difference is above that of the PUC case. Here, dual use is economically more attractive than smart charging according to PUC, since additional costs of the dual use cases, metering point operation, bidirectional charging stations, and possible aggregator costs should be considered. This means that for the FCR case, for example, these additional costs must not exceed 203 € per EV to generate a profit in 2020. These costs should not exceed 363 € to make the DUC-FCR case worthwhile compared to the PUC case.

It should be kept in mind that in this analysis we assumed that the revenues of the DUC Cases are equally distributed among all vehicles,

Table 7
Results of the five simulated cases for analysis of battery degradation with and without dual use operation.

Case	Lifetime in years	Mean SOC	EFC Total	Avg. EFC per year	Utilization ratio	Dual use ratio
UC	7.71 a	91.6 %	1,261	164	59.2 %	0 %
PUC	12.82 a	44.4 %	2,117	165	59.2 %	0 %
DUC-FCR	11.75 a	67.7 %	2,188	186	100 %	100 %
DUC-ID	7.43 a	69,4 %	2,358	317	69.9 %	26.3 %
DUC-DA	10.41 a	73,4 %	1,825	175	71.6 %	30.3 %

even though the EV under consideration is on the road 59% of the time. The aggregator could also distribute its revenue based on provisioning and therefore the simulated EV would likely generate less revenue. In addition, battery costs were assumed that do not necessarily correspond to the final customer prices due to, e.g., taxes. However, it can also be assumed that battery costs will continue to decrease in the future, so that a repurchase could possibly be below the assumed 2,052 €. On the other hand, FCR revenues could also decline further in the future due to market saturation. Moreover, the aging model used in this analysis is from the year 2014 and new battery cells are likely to degrade slower. This could make the DUC cases even more attractive. Finally, this analysis used a vehicle that is frequently on the road a lot with its battery already frequently cycled in primary use. This results in little time for dual use. An analysis with, for example, private vehicles that are idle 95% of the time could lead to different results.

5. Conclusion and outlook

This section summarizes the main findings of the paper and discusses the results. Moreover, it provides an outlook on further developments and emerging research questions.

5.1. Conclusion

In this work, we show that aggregators of EVs for V2G use can gain competitive advantages through optimized vehicle selection. Therefore, optimization methods are developed that determine which combinations of vehicles would be economically favored based on the power capability profiles of the vehicles. The power capability profiles used are determined from driving data of 468 commercial vehicles and explicitly presented in a previous publication [10]. As potential markets, FCR provision in Central Europe as well as arbitrage trading on the EPEX intraday continuous and day-ahead auction markets are analyzed.

The possible yearly revenues in the three markets vary from only 5–30 € per EV (day-ahead) to 220–380 € per EV (FCR), which answers research question 2 (RQ2). In all three markets, optimal pool composition can increase revenue per participating EV compared to random pools of the same number of vehicles. In the FCR market, revenue per vehicle can be increased by 72% with the optimal number of vehicles when using optimization compared to the mean of random pools. If, for example, 150 EVs are used to provide FCR, revenue can be doubled to tripled compared to a random pool selection. For arbitrage trading in the intraday continuous market, optimization achieves a 160% increase in revenue. In the day-ahead auction market, the increase in revenue is even larger with an almost 7-fold increase compared to random pools of the same number that could generate revenue. If, for example, 150 vehicles are optimized in intraday or day-ahead trading, revenues increase by 66% or 79%, respectively, compared to the average of random pools of the same size. In total, we show that aggregators of EV pools gain a competitive advantage through smart selection of vehicles (RQ1). This higher efficiency can bring a relevant market advantage for aggregators, since costs are incurred per connected vehicle (bidirectional charging station, metering equipment). Especially with a high penetration of EVs in the future and thus a large number of possible EVs for V2G, we expect that intelligent pool aggregation will be crucial for profitability. As the number of potential vehicles increases beyond the 468 EVs considered, the optimal number of EVs in the pool will also increase.

A direct comparison between the markets reveals that in 2020 the FCR provision is the most profitable application (RQ3). Here, revenues greater by a factor of 1.9 (vs. intraday) and 13.5 (vs. day-ahead) could have been achieved. However, it is worth mentioning that for smaller pools of EVs (<100) intraday and day-ahead markets are favorable as long as no taxes and fees have to be paid, since the FCR market requires a minimal provision of 1 MW. Alternatively, pools could merge to achieve the minimum power to provide FCR. In the arbitrage markets, seven times the revenue can be generated on the intraday continuous market compared to the day-ahead auction market. In addition, the intraday market with its 15 min provision time is more flexible than the day-ahead auction market with 1 h each.

While the optimization itself is limited to a revenue analysis, we also conducted a degradation study revealing additional costs from battery degradation. Here, an example driving profile and a provision of the three dual uses is simulated to account for additional battery degradation. Interestingly, dual use showed reduced degradation compared to uncontrolled charging in the FCR and the day-ahead case, which is attributed to the lower average SOC. For the intraday case, the lifetime is slightly reduced compared to uncontrolled charging. A primary use-oriented smart charging shows the least degradation (RQ4). Afterwards, the revenues on the markets are compared with the costs of degradation. The revenues clearly surpass the aging costs, in particular for the FCR and intraday cases. The day-ahead case is slightly worse than the smart charging case (RQ5).

5.2. Discussion

In the following section, we frame and discuss the results. First, it is important to explain that in the results presented, we maximize revenues (not profit) based on the power capability profiles (for FCR) or free cloud energy capacity and available power (for intraday and day-ahead) and average prices. Possible costs of the aggregator (e.g., fixed costs or costs for bidirectional charging stations) or due to the additional degradation of the batteries were neglected in the first analysis (Section 4.1). However, the exemplary simulation of vehicle battery degradation showed that market revenues could compensate for the additional degradation costs. In this example, we used one daily profile of a vehicle that is on the road for 60% of the time and already makes 165 equivalent full cycles per year even without V2G. To be able to depict degradation of vehicle batteries in particular more accurately, we will develop time series simulations in future publications that can simulate the retrieval and provision in more detail. In this work, however, the focus is on the optimization of EV pools. Regarding the fixed costs of aggregators, if our methodology is used, they could add their own costs to be covered by all participating EVs, which would create larger EV pools.

In terms of the markets under consideration, there are also a few points to note. On the one hand, the FCR provision neglects a possible necessary additional purchase on the spot markets. On the other hand, possible degrees of freedom in the provision of FCR are not considered, which might increase revenues. Furthermore, the arbitrage algorithm is rudimentary without a smart charging strategy. Incoming EVs are not discharged when the SOC is still high in order to have a larger free pool capacity. Instead, only the free cloud capacity that is available after primary use is utilized. This does not limit the EV owners in their mobility, but does lead to lower achievable revenues. Furthermore, lower purchase prices and higher sell prices than the mean prices could be obtained in the spot market by smart trading [70]. In addition, analogous to [70], it is assumed that no taxes and fees are incurred on the purchase of energy in spot market trading. Adding these taxes, which private households usually must pay, would make the arbitrage case unprofitable. In addition, differentiation between behind-the-meter (BTM) and in front-of-the-meter (FTM) must be taken into account in multi-use concepts [79]. This also applies to vehicles that charge energy through, e.g., FCR (FTM) and then use this energy for mobility (BTM). We address this issue in another recently published [80].

To solve the optimization problem, we used a genetic algorithm as described. This metaheuristic optimization does not necessarily find the global optimum, but, as shown in the results, a very good solution. Should aggregators use the method with a very high number of profiles, the runtime of the genetic algorithm will increase significantly. The runtime for the 468 profiles on one workstation was just under 2 h. Alternatively, the linear optimization presented in Section 3.1.3 can be performed iteratively for all possible numbers of EVs, which finds the global optimum, but leads to an even longer runtime.

Regarding the revenues that can be generated in the various markets in the medium to long term, it should be considered that potential revenues in the FCR market could continue to fall due to increasing market saturation. In contrast, price spreads on spot markets could continue to increase due to a further increase in renewable generators with fluctuating electricity generation. Consequently, the achievable revenues could converge and arbitrage on the spot markets could become economically more interesting. However, we conclude from the results presented that optimizing vehicle pools from an aggregator's perspective can be extremely economically rewarding in other markets as well.

5.3. Outlook

In this work, we presented the benefit of an optimal pool composition by means of optimization methods. In this section, possible further developments and emerging research topics are stated:

The *database* of the present work is formed by 468 commercial vehicles. An application of the methodology to private vehicles could also be interesting for aggregators. For implementation, however, these would have to be encouraged to participate through clever business models [15]. In addition, we expect that the potential of optimized pool composition will be even greater in practice with a larger database, if the aggregator can select vehicles specifically across the entire market. In addition, aggregators could also add stationary energy storage systems or renewable energy systems to their pools to exploit other flexibilities.

The *markets* analyzed in this paper are the FCR market in Germany and the EPEX Spot market. Beyond these markets, further balancing power markets such as automatic frequency restoration reserve (aFRR) could be analyzed. This market allows the provision of positive or negative power separately, which could allow EVs to be charged at low cost when negative control power is provided. However, the FTM-BTM issue would have to be considered and taxes and fees might have to be paid in arrears [80]. In addition, minimum bid sizes of, for example, 1 MW in the FCR market impose regulatory barriers for new players in the V2G field [81]. However, these barriers, especially for pools of EVs, have been recognized by the TSOs and could be reduced in the future [55]. We will analyze the impact of reduced minimum offer sizes on the FCR market in another future paper on the topic. Other interesting markets for V2G capable vehicles may be emerging flexibility markets in distribution grids. Furthermore, the methodology of the optimization methods could be applied to further international markets.

Regarding the *strategy* of the aggregator, spot markets are only used for arbitrage trading in this work. The vehicles are not discharged in a targeted manner, but only free capacities were used. A further development would be smart charging strategies. Those could first discharge the EVs after arrival and then charge them at night at low cost. However, power capability profiles are not sufficient for this and are to be further developed in the future based on time series simulations. These time series simulations could also be used to simulate and optimize the retrieval of EVs in a pool. For example, the degradation of the batteries could be considered. From the aggregator's point of view, a dynamic pool formation in which the vehicles are not assigned to a fixed market but switch variably between the markets could also be interesting. This could also be a response to expected market saturation effects at FCR [10,82].

Moreover, *business models* need to be developed that allow EVs to be applied in dual use. Here, for example, the aggregator could own the vehicle battery and lease it to the owner of the vehicle [83]. In addition, an aggregator could offer the vehicle owner discounted charging when participating in the pool compared to normal charging. Billing concepts could also be developed in which vehicles that contribute more to the pool power could generate higher revenues. Moreover, original equipment manufacturers could act as aggregators themselves, engaging vehicle buyers as long-term, permanent customers rather than just selling the vehicle [15]. For them in particular, the dual use of the vehicle battery in island grid operation during power outages could become a selling point.

Overall, the concept of dual use, meaning the switch of usage of EVs between mobility and V2G in idle times, offers a lot of potential for research and development and a potentially very large and lucrative market in the future.

CRediT authorship contribution statement

Benedikt Tepe: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Visualization. **Jan Figgener:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Visualization. **Stefan Englberger:** Methodology, Software. **Dirk Uwe Sauer:** Resources, Writing – review & editing, Supervision. **Andreas Jossen:** Resources, Writing – review & editing, Supervision. **Holger Hesse:** Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

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

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Appendix

A.1. Results of manually calculated optimization problems

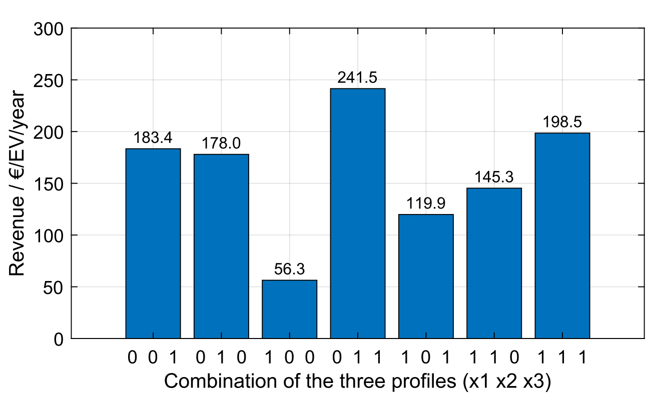

Fig. A1. Manual calculation of revenue per EV (FCR) and year for all combinations of the three EV profiles in Fig. 3.

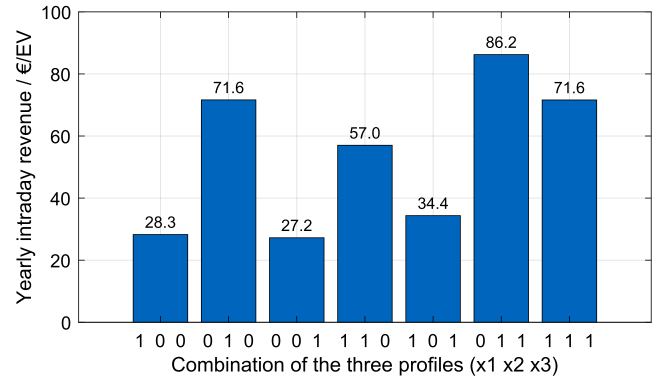

Fig. A2. Manual calculation of revenue (intraday continuous) per EV and year for all combinations of the three EVs in Fig. 6.

A.2. Profiles of degradation analysis

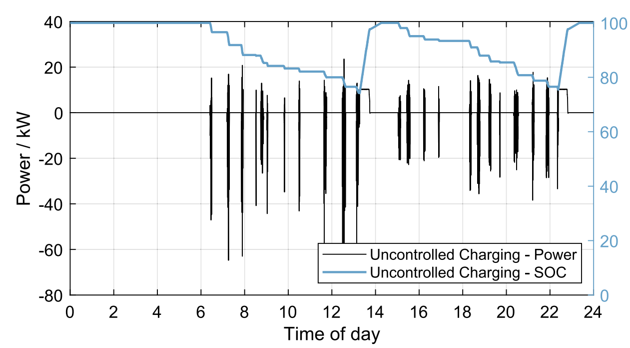

Fig. A3. Uncontrolled charging (UC) power and SOC.

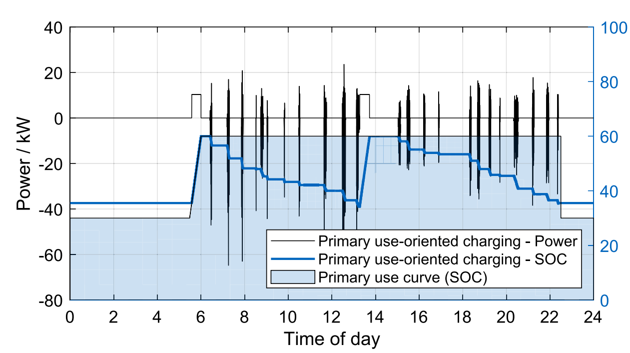

Fig. A4. Primary use-oriented charging (PUC) power and SOC.

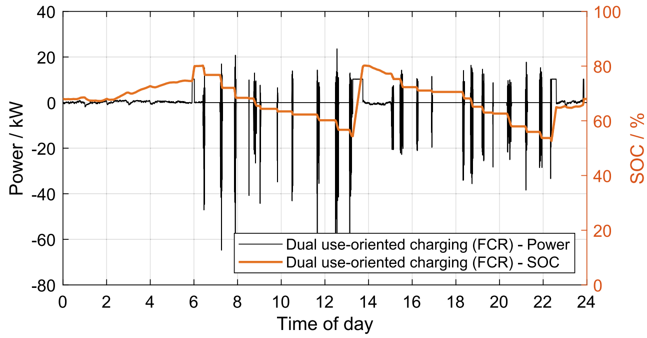

Fig. A5. Dual use-oriented charging for FCR provision (DUC-FCR) power and SOC.

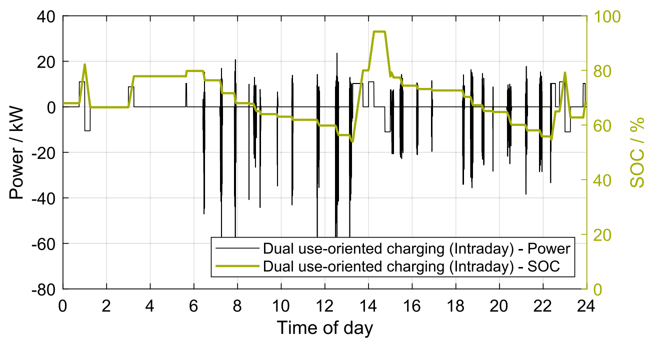

Fig. A6. Dual use-oriented charging for intraday continuous arbitrage (DUC-ID) power and SOC.

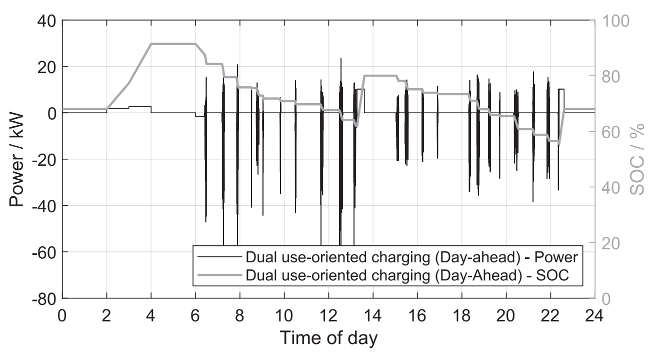

Fig. A7. Dual use-oriented charging for day-ahead auction arbitrage (DUC-DA) power and SOC.

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