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Electric vehicle multi-use: Optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context

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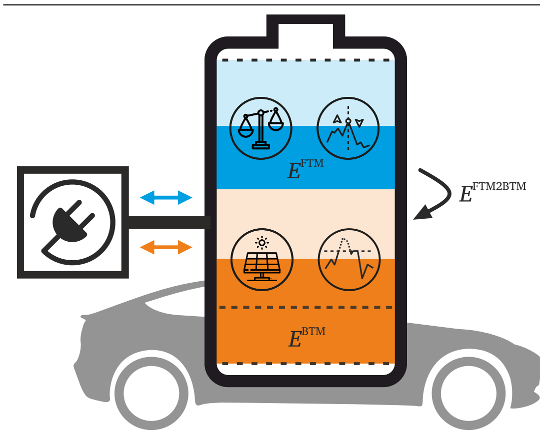
GRAPHICAL ABSTRACT



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ABSTRACT

Driven by the need for a sustainable energy transition and a paradigm shift in the energy and mobility sectors, the popularity of electric vehicles is on the rise. Learning curve effects and falling investment costs further accelerate the deployment of electric vehicles with lithium-ion batteries; and as a multi-purpose technology, they are predestined for serving multiple applications. In this work we present an electric vehicle multi-use approach for a German commercial electricity consumer with an electric vehicle fleet. We analyze which behind-the-meter and in front-of-the-meter applications are particularly suitable for electric vehicles from a techno-economic point of view. In addition to providing the mobility service, we investigate the applications self-consumption increase, peak shaving, frequency regulation, and spot market trading. For the implementation of the approach, we introduce a model predictive control framework in which a mixed-integer linear programming algorithm is combined with a semi-empirical degradation model. The approach is analyzed with the investigation of fleet sizes from 1 to 150 vehicles, different application combinations, possible energy shift between the energy partitions, bidirectional charging schemes, and degradation awareness formulations. The results show that the deployment flexibility and application synergies increase with the number of stacked services, leading to additional annual cash flows of up to 2224 EUR per electric vehicle as well as battery lifetime improvements.

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Nomenclature

Abbreviations

BTM	behind-the-meter
EFC	equivalent full cycle
EOL	end-of-life
EV	electric vehicle
FCR	frequency containment reserve
FTM	front-of-the-meter
MILP	mixed-integer linear programming
MPC	model predictive control
NMC	lithium–nickel–cobalt–manganese-oxide (LiNiCoMnO2)
PS	peak shaving
PV	photovoltaic
SCI	self-consumption increase
SMT	spot market trading
SOC	state of charge
SOH	state of health
V2G	vehicle-to-grid

Parameters & variables

$\mathbb{C}^{\text{degradation}}$	economic cost for battery degradation
$\mathbb{C}^{\text{PS}}$	economic cost for PS application
$\mathbb{C}^{\text{PS,optimal}}$	economic cost for PS application during optimized charging mode
$\mathbb{C}^{\text{PS,simple}}$	economic cost for PS application during simple charging mode
$\mathbb{C}^{\text{SCI}}$	economic cost for SCI application
$\mathbb{C}^{\text{SCI,optimal}}$	economic cost for SCI application during optimized charging mode
$\mathbb{C}^{\text{SCI,simple}}$	economic cost for SCI application during simple charging mode
$E^{\text{BTM,actual}}$	actual energy content at BTM partition
$E^{\text{BTM,purchase}}$	purchased BTM energy
$E^{\text{BTM,sell}}$	sold BTM energy
$E^{\text{BTM,usable}}$	usable energy content at BTM partition
E^{buffer}	buffer energy content
E^{drive}	energy consumption for mobility purposes
$E^{\text{drive,BTM}}$	BTM energy consumption for mobility purposes
$E^{\text{FTM,actual}}$	actual energy content at FTM partition
$E^{\text{FTM,usable}}$	usable energy content at FTM partition
E^{FTM2BTM}	energy shift from FTM to BTM partition
E^{nominal}	nominal energy content
$E^{\text{SMT,purchase}}$	purchased electricity for SMT application
$E^{\text{SMT,sell}}$	sold electricity for SMT application
E^{usable}	total usable energy content
η^{CH}	charging efficiency
η^{DCH}	discharging efficiency
f	grid frequency
f^{n}	nominal grid frequency
f^{DB}	frequency dead band
$P^{\text{BTM,CH}}$	charging power at BTM partition
$P^{\text{BTM,DCH}}$	discharging power at BTM partition
$\hat{P}^{\text{BTM}}$	PS threshold
P^{CH}	charging power
$P^{\text{CH,MAX}}$	maximum charging power
P^{DCH}	discharging power
$P^{\text{DCH,MAX}}$	maximum discharging power
P^{FCR}	provided power for FCR application
$P^{\text{FCR,MAX}}$	maximum provided power for FCR application
$P^{\text{FCR,MIN}}$	minimum provided power for FCR application
$P^{FCR,offer}$	offered power for FCR application
$P^{FCR,reserve}$	reserve power for FCR application
$P^{\text{FTM,CH}}$	charging power at FTM partition
$P^{\text{FTM,DCH}}$	discharging power at FTM partition
$\mathrm{p}^{\text{BTM,E,purchase}}$	energy-related price for purchased BTM electricity
$\mathrm{p}^{\text{BTM,E,sell}}$	energy-related price for sold BTM electricity
$\mathrm{p}^{\text{BTM,P}}$	power-related price for purchased BTM electricity
$\mathrm{p}^{\text{charges}}$	price charges to shift energy from FTM to BTM partition
p^{FCR}	remuneration price for FCR provision
$\mathrm{p}^{\text{SMT,purchase}}$	price for purchased electricity for SMT application
$\mathrm{p}^{\text{SMT,sell}}$	price for sold electricity for SMT application
$\mathbb{P}^{\text{FCR}}$	economic profit of FCR application
$\mathbb{P}^{\text{PS}}$	economic profit of PS application
$\mathbb{P}^{\text{SCI}}$	economic profit of SCI application
$\mathbb{P}^{\text{SMT}}$	economic profit of SMT application
σ	frequency droop for FCR application
$\text{SOC}^{\text{preference}}$	preferred minimum SOC
t	time step
$t^{\text{FCR,reserve}}$	reserve time for FCR application
x^{FCR}	integer variable that defines if FCR is active
x^{plugged}	integer variable that defines if EV is parked and connected
$x^{\text{SMT,purchase}}$	integer variable that defines if electricity is purchased during SMT
$x^{\text{SMT,sell}}$	integer variable that defines if electricity is sold during SMT

1. Introduction

Rising global awareness of the urgent need for a sustainable energy transition places increasing pressure on the energy sector to prioritize resource efficiency and ambitious sustainability targets [1]. This is accompanied by an increase in renewable energy [2] and a greater need for energy storage to balance the largely volatile renewable power generation [3]. Due to learning curve effects [4], battery cell prices have fallen significantly in recent years [5], with lithium-ion batteries enjoying especially strong growth [6]. One of their unique benefits is that battery storage systems can be used in a variety of applications, such as grid services with stationary battery storage or mobility provision in electric vehicles (EVs). In the stationary sector, it is now apparent that combining several applications on a single storage, or so-called multi-use [7], is economically viable [8], yet still hindered by regulation [9]. Continuous research and development in the field of battery EVs is expected to further increase the capacities of lithium-ion batteries used. Correspondingly, the annual demand for automotive battery capacity is projected to increase from 300 GWh in 2020 to between 1.6 and 3.2 TWh per year by 2030 [10]. These installed battery capacities offer enormous potential to substitute stationary storage systems since EVs are primarily purchased for mobility purposes but spend up to 96% of their lifetime parked and unused [11]. Through aggregator concepts [12], EVs can support the electricity grid during idle times by balancing power or storing renewable energy [13]. This is realized by using either smart unidirectional charging or vehicle-to-grid (V2G) technology. In the latter case, the vehicle's energy can be discharged into the grid and thus offers an enhanced flexibility potential compared to unidirectional charging [14]. Pools of EVs can participate in a variety of markets, such as ancillary service markets, during idle times [15].

With its fast response times [16], the lithium-ion storage technology is capable of providing a wide range of applications [17], making it a multi-purpose technology [18]. Due to global demand pull policies [19], increased deployment [20], and economies of scale [21], the investment attractiveness is continuously increasing [4]. Although battery energy storage systems have many advantages in comparison to other storage technologies, the technology can struggle with profitability issues when applied to single-use cases [22]. When serving one application only, storage systems often show low utilization [23] and a high share in idle times [24]. As lithium-ion batteries suffer from internal degradation processes [25], which also occur during idle times [26], the fact of a limited lifetime must be considered when defining the optimal deployment strategy [7]. Literature has shown that for stationary storage systems, serving multiple applications simultaneously can maximize the utilization [27] and therefore minimize the share of idle times [28]. Three multi-use types are identified – sequential, parallel, and dynamic multi-use – that differ in the temporal and physical allocation of the technical capacities of the storage system [27]. With its capability of providing consumer centered applications, but also grid and ancillary services [8], batteries yield economic value at different origins of the electricity value chain [9]. To comply with existing unbundling laws, a separation of value generation in the electricity value chain becomes necessary when serving multiple applications [7]. Thus, we distinguish between behind-the-meter (BTM) and in front-of-the-meter (FTM) applications [27]. Technically, this separation between BTM and FTM applications is achieved by dividing the physical storage into two virtual partitions and thus allocating the technical capacities – power and energy – of the system. With this stacking of applications on an energy storage system the economic value is maximized [29].

V2G describes a smart grid concept [15], where EVs are connected to the grid with the goal to provide value that goes beyond mobility provision [30]. This enables a more efficient management of electricity resources and better renewable energy integration [15], as well as the potential to mitigate future grid infrastructure investment costs [31]. EVs are an attractive option for these services as they are characterized by quick response times [11] and a high degree of geographic and temporal flexibility [32]. One approach for an intelligent integration of EVs is smart charging, which describes an unidirectional charging scheme that reduces charging costs and peak load by strategically timing the charging power [33]. This approach is comparatively easy to implement as it only requires a suitable charging controller instead of specialized hardware [34]. However, bidirectional charging also enables energy to be fed back into the grid, thus allowing the full spectrum and revenue of services available to conventional stationary storage systems [35]. This requires more complex, specialized bidirectional chargers [36] and can lead to increased battery aging [37], which poses a challenge for gaining user acceptance. Therefore, currently only few car manufacturers provide vehicles capable of bidirectional charging [30]. Furthermore, where traditional energy grids rely on centralized and deterministic grid architectures, V2G preferably utilizes a decentralized approach, in which an aggregator acts as a third party between multiple EVs and the grid operator [38]. This allows the aggregator to be treated similarly to a conventional ancillary service provider and allows an easier integration with reduced communication infrastructure requirements [39]. Aggregators are often necessary to meet the minimum power requirements and regulatory prerequisites that must be fulfilled to participate in existing markets [40]. Due to these reasons, V2G is especially interesting to commercial fleet operators [30], such as company fleets [41]. The economic viability of V2G has been examined in multiple studies with highly varying profitability results [42]. This is due to V2G viability being dependent on various factors regarding technology, market structure, policy, and business models [43]. Future changes that should be implemented to support the V2G concept include the avoidance of double taxation for energy charged and discharged, increasing the emphasis on smart grid solutions and implementing policies that favor small providers, such as lowering required bidding increments [43]. Furthermore, uniform technology standards for charging and communication infrastructure should be implemented [44].

Analogous to stationary storages, where multi-use is key to achieving profitability [19,45], the stacking of multiple applications is also an opportunity for EV owners and other involved parties to achieve greater profitability potential [13]. Whilst research has demonstrated that V2G can generate revenues for EV owners using single applications such as frequency regulation [46] or peak shaving [12], to the best of our knowledge, a viable *EV multi-use* approach has not yet been presented. The decisive factor here, is the analysis of which applications are appropriate for *EV multi-use* and how the approach can be successfully implemented using EVs [47].

This paper presents a methodology for *EV multi-use*, which considers technical, economic, and regulatory perspectives and constraints. To fulfill regulatory requirements of unbundling laws [9], the storage resources are separated into BTM and FTM applications. We focus on evaluating the following effects:

- Stacking of up to four additional applications on the EV battery, on top of the vehicle's mobility provision: self-consumption increase (SCI), peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT)
- Unidirectional charging versus bidirectional V2G operation
- Energy shift from in front-of-the-meter (FTM) to behind-the-meter (BTM) partition permitted or not permitted
- Battery degradation due to higher storage utilization

Our results demonstrate that *EV multi-use* – or the utilization of EV batteries for multiple applications in addition to mobility provision – is a viable technology that can boost profitability for EV owners and other stakeholders through a variety of application combinations. Utilizing a mixed-integer linear programming (MILP) model, the presented *EV multi-use* approach makes a valuable contribution to bridge existing literature gaps, by:

- Evaluating the combination of multiple value streams on a commercial EV fleet
- Distinguishing between behind-the-meter (BTM) and in front-of-the-meter (FTM) applications for EV fleets
- Allocating both the EV battery's power and energy capacities to each of its applications

The paper is structured as follows. In Section 2, we describe the value streams for EVs and review related literature. Section 3 explains the methodology of the analysis, the optimization algorithm, and the model predictive control (MPC) framework. The results of our analysis are presented in Section 4 and the conclusions are drawn in Section 5.

2. Value streams for electric vehicles

This section describes the five value streams that we investigate in this work. Besides the state of the art literature for the respective applications and use-cases, the mathematical formulation is described in the following subsections.

2.1. Mobility provision

Although vehicles spend approximately 96% of their lifetimes parked, providing mobility is their primary purpose [48]. The main categories of EV use types are domestic and commercial vehicles [30]. While the former do not usually follow any fixed schedules, commercial vehicles not only follow predictable patterns, but are also usually parked in the same area and characterized by fewer actors and more experience [30], making them particularly attractive for V2G concepts [41]. Further distinctions must be made in regard to vehicle usage patterns. Two main types of domestic driver categories are commuters and supplementary users; supplementary users are characterized by long plug-in times at home and occasional trips, while commuters show very predictable trips to their workplace on weekdays [35]. Using EVs in vehicle-to-building settings reveals economically interesting synergies between charging times, photovoltaic (PV) generation and building energy consumption [49].

V2G participation depends heavily on successfully mitigating social hurdles, such as range anxiety, which is why it is important to implement rules concerning a preference state of charge (SOC) [50]. This is implemented in our optimization framework in the form of soft constraints that apply opportunity costs to energy levels that are below the preference SOC threshold (cf. Eq. (1)). Here, the actual energy content of the BTM partition and the buffer energy must be equal to or greater than the energy content at the preference SOC level. This is set to 20% [51], corresponding to approximately 64 km range when regarding a battery with a capacity of 80 kWh and a conservative average energy consumption of 0.25 kWh/km [52]. With the consideration of the binary variable x^{plugged}, the opportunity costs for the buffer energy only apply when the vehicle is connected to a charging port, which leaves the driving state of the vehicle unaffected by the constraint. For the mobility provision the BTM energy is regarded, as the FTM energy is spared certain surcharges and may not be used for driving.

$$E^{\text{nominal}} \cdot \text{SOC}^{\text{preference}} \cdot x_t^{\text{plugged}} \leq E_t^{\text{BTM,actual}} + E_t^{\text{buffer}} \tag{1}$$

2.2. Self-consumption increase

An increasing number of countries have implemented feed-in-tariffs and demand pull policies to incentivize an increase in renewable energy technologies [19]. The gap that arises between the relatively low price granted by subsidies ($\text{p}^{\text{BTM,E,sell}}$) and the retail purchase price ($\text{p}^{\text{BTM,E,purchase}}$), provides prosumers with an incentive to increase self-consumption [53]. As solar panel prices decrease and private and commercial buildings are thus increasingly equipped with micro generation [45], storage systems become a promising tool to perform SCI and thus reduce electricity costs [35] and carbon emissions [54]. This is especially economically interesting in countries with high retail electricity prices [45]. A further benefit of SCI is a reduction in stress on the electricity distribution grid [54], especially through peak PV generation, which mitigates future infrastructure investment costs and ensures a more efficient grid operation [55].

When applied to V2G concepts, the viability of SCI becomes especially dependent on mobility behavior [54], as the vehicle plug-in times should match times of PV generation [56]. This can be difficult with typical commuter driving profiles [35]. In home applications with non-commuters, V2G based SCI can render conventional stationary storage systems obsolete [35].

$$\mathbb{C}_t^{\text{SCI}} = E_t^{\text{BTM,purchase}} \cdot \text{p}^{\text{BTM,E,purchase}} - E_t^{\text{BTM,sell}} \cdot \text{p}^{\text{BTM,E,sell}} \tag{2}$$

$$\mathbb{P}_t^{\text{SCI}} = \mathbb{C}_t^{\text{SCI,simple}} - \mathbb{C}_t^{\text{SCI,optimal}} \tag{3}$$

In our paper, workplace SCI with an aggregated fleet of EVs is considered. To quantify the profit from this application, the total optimized electricity cost is calculated as the difference between the purchase costs and revenues from selling energy, as in Eq. (2). As SCI is a consumer-oriented application, all considerations here refer to the BTM partition. To calculate the profit, the electricity costs when performing optimized SCI are compared to the costs of a reference case, in which the EVs are simply charged to maximum SOC whenever possible (cf. Eq. (3)).

2.3. Peak shaving

Contrary to residential electricity consumers, commercial players often consume significant levels of electricity from the grid [57]. For this reason, such consumers are not only charged for the consumed energy, but also for their peak power demand [57], which constitutes significant costs [58]. In the case of Germany, power demand is averaged over 15 minute intervals and the peak power over the entire billing period is utilized to determine the power charges, which consumers with an annual consumption above 100 MWh are required to pay [7]. Besides high consumer costs, large power spikes also constitute more stress on the grid [49], which will require an increase in power generation or an upgrade of the grid infrastructure [59]. To avoid these problems, PS is utilized, which describes strategies to reduce the peak power demand. In the past, this has been practiced among other by deploying diesel generators [57]. For the future however, demand side management strategies and energy storage systems [60], especially batteries, have been proposed [58]. With the addition of EVs and potential uncontrolled charging simultaneity, the problem of peak loads is further exacerbated [49]. Therefore, to mitigate these problems, optimized V2G strategies can perform PS [49]. While this application is argued to be of high value for V2G, it can be very energy intensive, which can risk excessively discharging the EV battery [11]. Since PS is an application that is only required during demand peaks [60], it naturally lends itself to multi-use approaches [7]. With enough participating vehicles, V2G can completely replace other methods of performing PS [61].

To effectively perform PS, precise predictions of power peaks are vital, since the battery must provide the energy and power required to fully cap the peak [57]. Therefore, it is also essential to define an appropriate power threshold, above which PS is applied (cf. Fig. 1). An exceedingly low threshold results in a large energy demand for the PS application and excessively drains the battery, whereas a too high threshold leaves PS potential untapped. For this reason, the PS threshold, $\hat{P}^{\text{BTM}}$, is included as a decision variable in our optimization framework.

$$\mathbb{C}^{\text{PS}} = \hat{P}^{\text{BTM}} \cdot \text{p}^{\text{BTM,P}} \tag{4}$$

$$P_t^{\text{BTM,purchase}} - P_t^{\text{BTM,sell}} \leq \hat{P}^{\text{BTM}} \tag{5}$$

$$\mathbb{P}^{\text{PS}} = \mathbb{C}^{\text{PS,simple}} - \mathbb{C}^{\text{PS,optimal}} \tag{6}$$

The basis for the PS optimization is the calculation of peak power costs as the product of the highest power peak and the power price in Eq. (4). This power peak is embedded in a constraint, where it serves as the upper bound of the difference between purchased and sold BTM power, as shown in Eq. (5). As for the other BTM application, SCI, the profit from PS is derived from the cost difference between the optimized and the reference case (cf. Eq. (6)).

2.4. Frequency containment reserve

Another promising V2G application is the provision of regulation power to stabilize the grid frequency [62], as this requires high rates of power within short time periods, which EVs are capable of providing when connected to the grid [40]. Ancillary service markets are relatively mature and already established in several countries [22]. With these services the grid frequency in the European network of transmission system operators for electricity (ENTSO-E) is kept within a ±10 mHz deadband zone around the nominal frequency of 50 Hz [63].

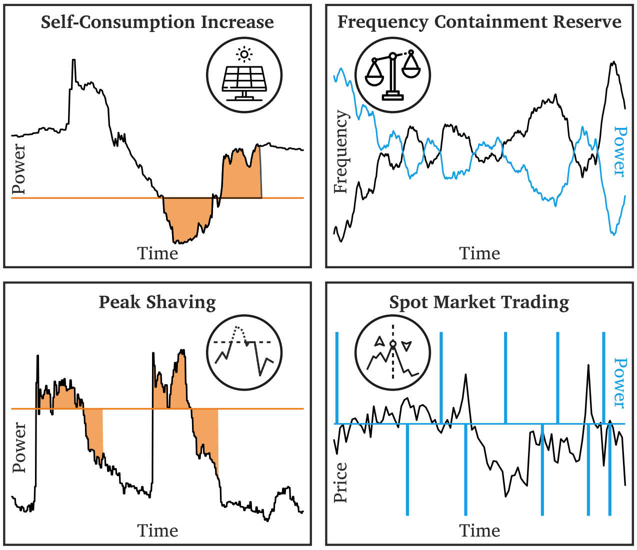

Fig. 1. Schematic illustration of the four grid applications: self-consumption increase (SCI) profits from zero crossings of the residual load. During peak shaving (PS) high load peaks are capped by the energy storage system. Frequency containment reserve (FCR) describes the provision of power to stabilize the grid frequency. To maximize the profitability, electricity is purchased and sold using volatile price signals during spot market trading (SMT).

To do so, the electricity balancing products are divided into frequency containment reserve (FCR), frequency restoration reserve and replacement reserve [64]. Of these products, primary control reserve under the FCR category is the most economically interesting in central Europe [27]. As the penetration of renewable energy sources increases and traditional synchronous generators become fewer in number, the need for FCR through storage systems is expected to grow significantly [65]. However, a challenge may arise in the future due to market saturation [12], which leads to sinking FCR remuneration [27] and a decline in revenue earning potential [22]. FCR must be provided over 4 h time blocks and the participating storage system must be designed to provide the allocated power for at least 15 min ($t^{\mathrm{FCR,reserve}}$) [63]. Eq. (7) constrains the energy committed to the FCR application to never exceed the allocated actual energy for the FTM partition, while also limiting the latter, so that the same amount of committed energy can also still be charged into the usable FTM partition. Thus, both positive and negative FCR energy can be provided, as FCR is a symmetric product.

$$P_t^{\mathrm{FCR,offer}} \cdot t^{\mathrm{FCR,reserve}} \leq E_t^{\mathrm{FTM,actual}} \leq E_t^{\mathrm{FTM,usable}} - P_t^{\mathrm{FCR,offer}} \cdot t^{\mathrm{FCR,reserve}} \tag{7}$$

$$P_t^{\mathrm{FCR,MIN}}(\mathrm{f}_t, \mathrm{f}^{\mathrm{n}}, \mathrm{f}^{\mathrm{DB}}, \sigma, P_t^{\mathrm{FCR,offer}}) \leq P_t^{\mathrm{FCR}} \leq P_t^{\mathrm{FCR,MAX}}(\mathrm{f}_t, \mathrm{f}^{\mathrm{n}}, \mathrm{f}^{\mathrm{DB}}, \sigma, P_t^{\mathrm{FCR,offer}}) \tag{8}$$

Due to regulatory constraints when regarding assets with limited energy capacities such as batteries, an additional 25% of the power, based on the offered FCR power, is guaranteed for scheduled transactions to keep the SOC within the permitted range [63]. In a practical implementation, such assets would also need to take lag effects into account, which can arise through scheduled transaction market or energy management system delays [63]. The provided power can furthermore be overfulfilled by 20%. Together with the grid frequency and the degrees of freedom of the application, the lower and upper bounds for the FCR power provision are derived, as shown in Eq. (8). The power is calculated as a function of the frequency f_t at time t, the nominal grid frequency f^{n} of 50 Hz, the deadband frequency f^{DB} of ±10 mHz, the frequency droop σ of 0.4% and the offered FCR power $P^{\mathrm{FCR,offer}}$.

Finally, the profit from FCR is calculated as the product of allocated FCR power and the respective FCR market remuneration in Eq. (9).

$$\mathbb{P}_t^{\mathrm{FCR}} = P_t^{\mathrm{FCR,offer}} \cdot \mathrm{p}_t^{\mathrm{FCR}} \tag{9}$$

FCR has been predicted to become one of the most interesting V2G applications [13]. Previous projects examining V2G based FCR, such as the Parker project, show that this application can be economically viable for EVs, with said project demonstrating average annual revenues of 1860 EUR per vehicle per year [47]. This however depends on local market conditions, business models and necessary infrastructure investments, which could hinder V2G FCR viability [66]. An increasing penetration of EVs without the possibility of providing frequency regulation services could however be detrimental to power system stability [38].

2.5. Spot market trading

Arbitrage trading utilizes electricity price differentials to achieve profit or mitigate charging costs [22], as shown in Fig. 1. In the past, SMT has not been attractive, especially in single-use scenarios, due to low market price spreads not justifying the increased degradation [22]. Recent developments, including decreasing FCR remunerations and growing spot market price spreads [27], render SMT a promising candidate for storage application, in part due to an increasing participation of renewable energy [67]. It could be especially interesting in multi-use concepts, for example together with FCR, where SMT is used to balance the SOC and compensate for efficiency losses [68]. While uncontrolled EV charging leads to increased electricity prices, V2G is predicted to have a smoothing effect on spot market prices [69]. This is especially attractive for the further implementation of renewable energy sources, as V2G can help alleviate price drops from surplus feed-in times [69]. The relevant markets in Germany are the day-ahead auction, the intraday auction, and the intraday continuous market [7]. Due to its volatile price signals, the intraday continuous market is well-suited to the high responsiveness of lithium-ion batteries [27], which is why we chose it for further analysis.

Eq. (10) establishes that within one time step, t, electricity can either be purchased, sold, or not traded. Here, $x_t^{\mathrm{SMT,purchase}}$ and $x_t^{\mathrm{SMT,sell}}$ are binary variables representing whether electricity is sold or purchased.

$$x_t^{\mathrm{SMT,purchase}} + x_t^{\mathrm{SMT,sell}} \leq 1 \tag{10}$$

The profit of the SMT application is defined in Eq. (11) as the difference between the revenue from sold and the cost of purchased electricity.

$$\mathbb{P}_t^{\mathrm{SMT}} = E_t^{\mathrm{SMT,sell}} \cdot \mathrm{p}_t^{\mathrm{SMT,sell}} - E_t^{\mathrm{SMT,purchase}} \cdot \mathrm{p}_t^{\mathrm{SMT,purchase}} \tag{11}$$

2.6. Further value streams

Beside the applications analyzed in this paper, several alternative value streams for EVs have been identified in literature and projects. For instance, with suitable charging hardware, V2G can be used to provide reactive power to help stabilize the grid voltage [15]. V2G is also an option to reduce grid congestion and thus mitigate expensive redispatch measures [31]. Furthermore, EVs can act as an emergency power supply when deployed in vehicle-to-building concepts [70]. When multiple EVs are connected, they can be used for peer-to-peer energy trading [71] or to supplement decentralized electricity grids by providing black start capability and other grid ancillary services [72]. Additionally, EVs can be utilized as mobile power supply units to provide electricity for different purposes, such as machinery and tools [47].

3. Methods

We develop a MILP framework to evaluate the techno-economic effect of *EV multi-use*. Combined with a MPC algorithm, the MILP optimization is conducted at regular intervals. This approach allows for the optimal scheduling and allocation of power and energy of the EV fleet, as well as a detailed calculation of the battery properties, such as the battery state of health (SOH) [7].

For the study, a German commercial building with a company EV fleet of privately used vehicles and respective charging stations at work is assumed. In this use case, the vehicles' idle time whilst parked at the office location is utilized to generate value by serving additional applications. The BTM electricity is traded with an energy retailer, using 0.2 EUR/kWh and 0.03 EUR/kWh for the purchase and remuneration price [73,74]. In addition to BTM, the company's EVs can also use FTM electricity to serve the FCR and SMT applications. A generation profile from a PV generator with 120 kW peak power [35] and a commercial load profile with an annual consumption of 500 MWh is applied [75]. The energy consumption for mobility purposes and the corresponding EV plug-in times at the commercial building are derived using the tool *emobpy* [76]. *emobpy* is an open-access tool for creating battery electric vehicle time series based on empirical data. 150 annual profiles, with the driving pattern and plug-in patterns at work, were chosen to form the basis of this analysis. For each EV, the annual driving distance is normally distributed around 15 000 km [77] with a usable battery capacity of 80 kWh and a conservative average consumption of 250 Wh/km [52]. For the FCR and SMT applications, price profiles from 2020 [74] and frequency profiles from 2019 are applied [78]. The intraday continuous market data is characterized by multiple price signals, such as low, index, and high price. Literature has shown that the economic potential of the SMT application is very limited when using the index price [7]. On the other hand, the use of high and low price signals is difficult, as a very accurate price prediction is necessary. For these reasons, the average price signal of the low and index price is used for the lower bound of the price corridor. Analogously, the average of index and high price is applied for the upper bound.

3.1. Mixed-integer linear model

The objective function, Eq. (12), maximizes the techno-economic potential of the energy system. All the presented variables in Eq. (12) represent decision variables of the optimization problem, excluding the charging efficiency η^{CH} and $\mathrm{p}^{\mathrm{charges}}$. For the optimization horizon the optimal operation strategy is calculated, which optimizes the charging power and the allocation of the EV fleet's capacities simultaneously. Therefore, the total profit (= revenue − cost), sum of all applications, is maximized. Under current regulatory constraints, energy exchange between FTM and BTM partitions is prohibited [79], however, this paper also analyzes the effects that would occur if this transfer is allowed for driving purposes. Thus, the energy that is shifted from FTM to BTM partition, E^{FTM2BTM}, is considered in the objective function. Since the levies and surcharges for FTM electricity are lower compared to those of BTM, this economic difference must be considered when the shift from FTM to BTM energy is permitted. As the energy losses for charging FTM energy into the EV battery are also purchased with reduced levies and surcharges, this cost correction is likewise applied to the charging losses. To prevent arbitrage in the model, these additional costs for energy shifting are subtracted from the SCI application profit (cf. Eq. (13)). This is an extension of the simple SCI profit function without permitted energy shift (cf. Eq. (3)). To avoid uneconomical energy throughput and thus accelerated degradation, the opportunity costs for degradation are also implemented in the main function.

$$\max\ z\ ,\ \ z = \sum(\mathbb{P}_t^{\mathrm{SCI}} + \mathbb{P}^{\mathrm{PS}} + \mathbb{P}_t^{\mathrm{FCR}} + \mathbb{P}_t^{\mathrm{SMT}} - \mathbb{C}_t^{\mathrm{degradation}}) \tag{12}$$

$$\mathbb{P}_t^{\mathrm{SCI}} = \mathbb{C}_t^{\mathrm{SCI,simple}} - \mathbb{C}_t^{\mathrm{SCI,optimal}} - E_t^{\mathrm{FTM2BTM}} \cdot \frac{1}{\eta^{\mathrm{CH}}} \cdot \mathrm{p}^{\mathrm{charges}} \tag{13}$$

For the purposes of the model developed in this paper, a few definitions and distinctions must be made. The EVs' batteries are partitioned into clearly distinguishable virtual FTM and BTM partitions [7], to comply with existing unbundling laws and separately allocate system power and energy [8]. BTM applications are generally consumer-oriented and serve to maximize the economic result of the storage system stakeholder. These applications are charged fully with all applicable grid charges, surcharges, and taxes and in this paper include SCI and PS. FTM applications on the other hand serve to stabilize the electricity system and usually only have limited charges applied to them, as the energy is not directly used for consumption purposes. In this paper, these applications are FCR and SMT.

On the EV level the nominal energy describes the rated energy content of the battery, while the usable energy content is limited by battery degradation and SOC boundaries. The actual energy content describes the stored energy at the current SOC. The separation into FTM and BTM partition is shown in Eq. (14), while Eqs. (15) and (16) determine that the actual energy content cannot exceed the usable energy content of the respective partition.

$$E_t^{\mathrm{usable}} = E_t^{\mathrm{BTM,usable}} + E_t^{\mathrm{FTM,usable}} \tag{14}$$

$$E_t^{\mathrm{BTM,actual}} \leq E_t^{\mathrm{BTM,usable}} \tag{15}$$

$$E_t^{\mathrm{FTM,actual}} \leq E_t^{\mathrm{FTM,usable}} \tag{16}$$

For each time step t, the entire usable energy is allocated to either of the two partitions ($E^{\mathrm{BTM,usable}}$ and $E^{\mathrm{FTM,usable}}$), so that the partitioning of the storage system is a result of the optimization process and depends on the constraints regarding each application. As part of the usable energy partition the actual energy content ($E^{\mathrm{BTM,actual}}$ and $E^{\mathrm{FTM,actual}}$) describes the energy that is stored in the respective usable partition. In this study, we defined the start value of the actual energy content with 70% SOC.

Eqs. (17) and (18) track the actual energy content of the two partitions and guarantee energy conservation within the battery. For both partitions, the energy content at time t is based on the previous energy content at time $t-1$ and the charged and discharged energy. To consider the energy losses during charging and discharging, η^{CH} and η^{DCH} are defined with 89.4% efficiency [80]. At the BTM partition the variable $E_t^{\mathrm{drive,BTM}}$ defines the energy that is discharged from the battery partition and utilized for mobility purposes.

$$\begin{aligned} E_t^{\mathrm{BTM,actual}} &= E_{t-1}^{\mathrm{BTM,actual}} + E_t^{\mathrm{BTM,CH}} \cdot \eta^{\mathrm{CH}} \\ &\quad - E_t^{\mathrm{BTM,DCH}} \cdot \frac{1}{\eta^{\mathrm{DCH}}} - E_t^{\mathrm{drive,BTM}} \end{aligned} \tag{17}$$

$$\begin{aligned} E_t^{\mathrm{FTM,actual}} &= E_{t-1}^{\mathrm{FTM,actual}} + E_t^{\mathrm{FTM,CH}} \cdot \eta^{\mathrm{CH}} \\ &\quad - E_t^{\mathrm{FTM,DCH}} \cdot \frac{1}{\eta^{\mathrm{DCH}}} - E_t^{\mathrm{FTM2BTM}} \end{aligned} \tag{18}$$

When the use of FTM energy for mobility services is permitted by the model, it is still guaranteed that no energy is directly shifted from the FTM to BTM partition, as this would violate unbundling laws. Instead, the stored FTM energy can be taken from the FTM partition and directly utilized to propel the vehicle (BTM application), as shown in Eq. (19).

$$E_t^{\mathrm{drive}} = E_t^{\mathrm{drive,BTM}} + E_t^{\mathrm{FTM2BTM}} \tag{19}$$

Besides the partitioning of energy, a distinction between FTM and BTM power is also applied, which is reflected in Eqs. (20) and (21). For the upper bound of the charging and discharging power, P^{CH} and P^{DCH}, 22 kW is assumed. The charging behavior is hereby implemented

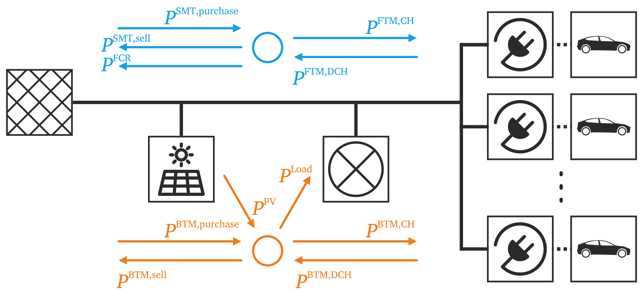

Fig. 2. Illustration of the physical power flows between the grid, photovoltaic (PV) generator, load, chargers, and electric vehicles (EVs). The arrows in orange and blue highlight the node constraints at the behind-the-meter (BTM) and in front-of-the-meter (FTM) partitions.

as a square profile, in which the optimized charging power under said constraints is applied constantly for the respective time step.

$$P_t^{CH} = P_t^{BTM,CH} + P_t^{FTM,CH} \tag{20}$$

$$P_t^{DCH} = P_t^{BTM,DCH} + P_t^{FTM,DCH} \tag{21}$$

It must be emphasized that applications and services, other than mobility, are served only if the EV is connected to the power grid. To implement this in the model, the charging and discharging power, P_t^{CH} and P_t^{DCH}, are set to 0 if the vehicle is not connected ($x_t^{plugged} = 0$).

To guarantee that BTM and FTM power flows and services do not mix, separate node constraints are added (cf. Fig. 2). On the BTM partition, the power flows from the PV generator, energy consumption of the commercial building, the charging and discharging power to and from the EV chargers, as well as the power flows to and from the grid, $P^{BTM,sell}$ and $P^{BTM,purchase}$, are balanced in Eq. (22). These and all following power values correspond to the related energy values, such as $E^{BTM,sell}$ and $E^{BTM,purchase}$, which are defined in the nomenclature table.

$$P_t^{PV} + P_t^{BTM,DCH} + P_t^{BTM,purchase} = P_t^{Load} + P_t^{BTM,CH} + P_t^{BTM,sell} \tag{22}$$

The FTM node constraint considers the converging power flows of the FCR and SMT applications and the exchange with the superordinate grid (cf. Eq. (23)).

$$P_t^{FTM,DCH} + P_t^{SMT,purchase} = P_t^{FTM,CH} + P_t^{SMT,sell} + P_t^{FCR} \tag{23}$$

In addition to the FTM node constraint, Eq. (24) limits the power utilized for the FCR allocation to comply to the FCR market regulations. Here $p^{FCR,reserve}$ is the aforementioned 25% reserve power for scheduled transactions on the spot market. The upper bound is hereby the minimum of the charging and discharging power, as the FCR application is a symmetrical product [63].

$$P_t^{FCR,offer} \cdot (1 + p^{FCR,reserve}) \le \min\{P^{CH,MAX}, P^{DCH,MAX}\} \tag{24}$$

3.2. Model predictive control

An important aspect for the operation strategy of storage systems is the prediction quality of the respective input data, such as power demand, PV generation and driving behavior. In this model, perfect forecast is assumed within the defined optimization horizon t^{OH}, of 24 h. With every rolling horizon, t^{RH}, of 8 h, the input data is updated, and a new optimization is conducted (cf. Fig. 3). Given this MPC framework, the algorithm allows the handling of prediction values. Due to the overlap of optimization and rolling horizon, the framework is less prone to prediction errors, as the operation strategy is regularly re-optimized.

To enable a comprehensive techno-economic analysis, the MPC framework combines the MILP optimization algorithm with a semi-empirical aging model. Therefore, the MILP considers opportunity costs

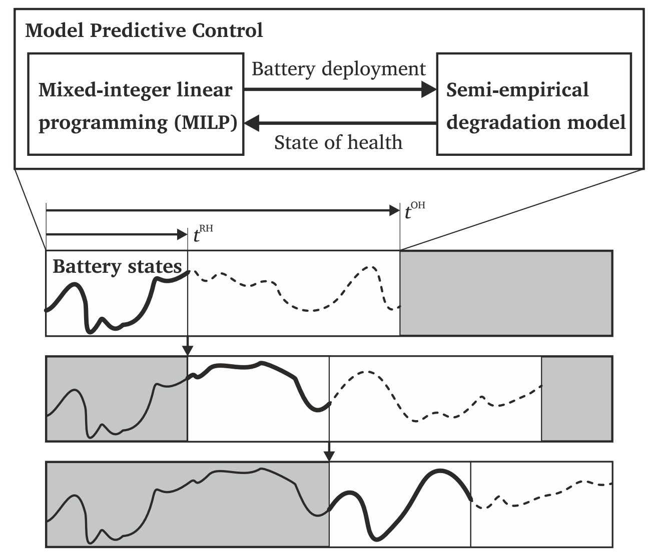

Fig. 3. The mixed-integer linear programming (MILP) algorithm and the semi-empirical degradation model are embedded in the model predictive control (MPC) framework. Within the MPC framework, the battery deployment and state of health (SOH) of the electric vehicles (EVs) are calculated and exchanged. The MPC is triggered with each new rolling horizon, t^{RH}, and a new optimization with the defined optimization horizon, t^{OH}, is conducted to calculate the optimal battery states.

from degradation in the objective function (cf. Eq. (12)). Thus, the model is made degradation aware, which leads to a reduction in battery aging through potentially excessive serving of grid applications [7]. For the calculation of the cycle opportunity costs an expected equivalent full cycle capacity of 1000 cycles until the battery's end-of-life [81] and battery investment costs of 200 EUR/kWh are assumed [5].

The modeled EV batteries are assumed to consist of cells with a lithium–nickel–cobalt–manganese-oxide cathode and a graphite anode, also abbreviated as NMC cell chemistry [25]. These batteries are frequently used in automotive applications, due to their high energy densities [82]. For this cell chemistry a semi-empirical aging model according to [25] is implemented. For the degradation modeling, the charge throughput and time-related parameters are especially important assumptions for the cycle and calendar degradation respectively. Here, the charge throughput and time relationship, introduced in [25] are defined as $Q^{0.55}$ and $t^{0.75}$. For the ambient temperature, a German temperature profile is considered [83]. The battery end-of-life is defined at 80% remaining capacity, as nonlinear degradation mechanisms may lead to accelerated aging beyond this point and battery safety concerns become more prominent at low SOH levels [81].

3.3. Scenarios and performance indicators

To examine the economic potential of application stacking in V2G, scenarios are constructed to observe the effects of different operation strategies. This primarily concerns different combinations of served applications, starting with only BTM applications, and then gradually adding FCR and SMT. Furthermore, as it has been argued that unidirectional smart charging could cover a large percentage of potential V2G value [13], simulations with and without bidirectional charging are performed and results assessed. Additionally, we analyze the merit of enabling or disabling FTM to BTM energy exchange as a further parameter. Finally, the effect of degradation awareness on revenue and lifetime is analyzed. The resulting scenarios are listed in Table 1, with the simple charging reference case *S0* forming the benchmark. The scenarios are characterized as follows:

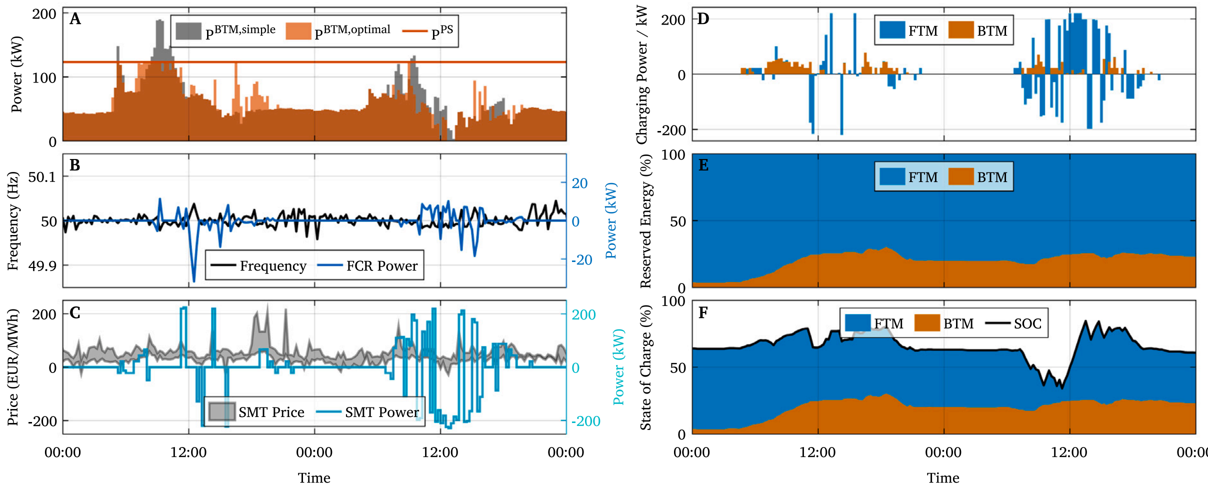

Fig. 4. Optimization framework outputs of an *EV multi-use* operation strategy with SCI, PS, FCR, and SMT. A two day excerpt is shown for: **A** the residual load on the BTM partition and the respective PS threshold; **B** grid frequency input profile and the FCR power provided by the EV fleet; **C** price corridor on the intraday continuous market and the power traded; **D** BTM and FTM charging power; **E** BTM and FTM energy content allocation; and **F** average state of charge (SOC) of the EV fleet and the respective energy allocation.

- Reference scenario *S0* uses a simple unidirectional plug and charge approach that charges the battery with maximum power whenever possible, maximizing the SOC level of the EV battery when connected to the grid. We chose this reference scenario due to its simplicity, however, alternative reference scenarios with more favorable effects on battery lifetime exist.
- Scenarios *S1* – *S8* follow an optimized charging strategy that is provided by the MPC framework. Here the objective function (cf. Eq. (12)) is applied to calculate the optimal operation strategy for the EV fleet, as shown in Fig. 4.
- To analyze the added value from bidirectional charging scenarios *S2* – *S8* are applied with the V2G technology, allowing power flows from the vehicle to the grid.
- The energy shift from the FTM to the BTM partition is allowed and analyzed in scenarios *S4*, *S6*, and *S8*.
- To study the effects with different EV fleet sizes the number of participating EVs varies from 1–150, resulting in energy and power capacities of up to 12 MWh and 3.3 MW.

For the techno-economic analysis, four key performance indicators are discussed: the annual and discounted cash flow per EV, the equivalent full cycles (EFC), and the average end-of-life (EOL) of the EV battery. Here, the annual cash flow is defined as the cash flow change between a scenario and the reference *S0*. For the discounted cash flow calculation until the EV battery's EOL [7], a 6% interest rate is specified [84]. The framework calculates the corresponding cash flows for the individual applications with the profit functions presented in Section 2. To design a comprehensive techno-economic analysis for EVs, the battery life must be considered in addition to cash flow. For this reason, the battery's energy throughput in EFC and the battery lifetime are also analyzed.

The presented methodology was developed in a MATLAB environment and is available upon request from the lead author.

4. Results

To compare the scenarios, simulations until the EVs' EOL are performed in the described commercial setting. The cash flows and lifetimes are averaged over the entire fleet and regarded on a per vehicle basis in the following sections. Although there are dependencies between the evaluations in the scenario matrix, the individual effects and their interrelationships are explained in the following subsections.

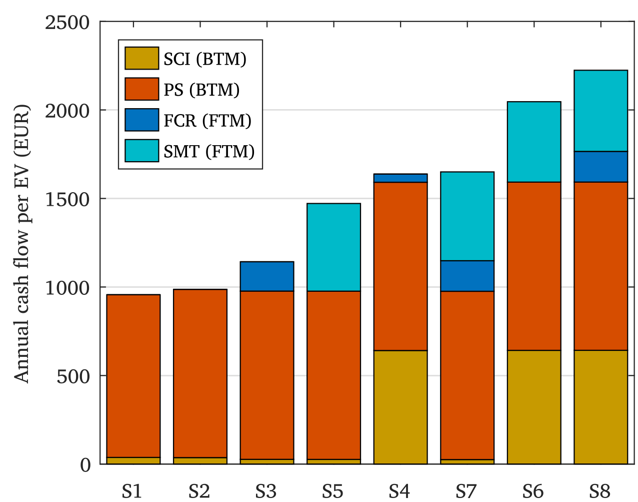

Fig. 5. Annual cash flow increase per electric vehicle (EV) compared to reference scenario *S0*. Here, the fleet size is 10 EVs.

4.1. Economic attractiveness of the value streams

As Fig. 5 shows, there is a clear hierarchy regarding the generated revenue per served application. The application with the highest revenue is PS, followed in this order by SCI and SMT, with FCR making up the least interesting application, economically. In cases with deactivated energy shift from FTM to BTM however, SMT and FCR achieve more revenue than SCI.

This pronounced attractiveness of PS is explained by a few factors. Firstly, the regarded case of a commercial player is especially conducive to the PS application, with a combination of an intrinsically high building energy demand and a high potential of power peaks due to the need to charge a fleet of electric vehicles at the same location. Secondly, the PS profit describes the cost savings through the optimized operation over the reference scenario *S0*, in which the EVs' SOC is maximized, leading to high power peaks.

With demand pull policies in place, increasing consumption from self-generated electricity becomes economically attractive, which leads to the high revenue generated through SCI in this model. SCI profit is also calculated in reference to the same base case as PS, which further

Table 1
Overview of the analyzed *EV multi-use* scenarios with the applications SCI, PS, FCR, and SMT. During V2G operation, bidirectional charging is enabled. Column FTM2BTM determines if an energy shift from the FTM to BTM partition is allowed. The cash flow defines the annual cash flow increase per vehicle in comparison to the reference scenario *S0*. The equivalent full cycles (EFC) define the annual energy throughput. The numbers shown refer to a fleet of 10 EVs.

Scenario	Applications	Optimized charging	V2G	FTM2BTM	Cash flow (EUR/a)	EFC/a	EOL (a)
S0	–	no	no	no	0	47.4	7.9
S1	SCI, PS	yes	no	no	956	47.4	11.8
S2	SCI, PS	yes	yes	no	987	47.5	11.6
S3	SCI, PS, FCR	yes	yes	no	1143	54.7	9.8
S4	SCI, PS, FCR	yes	yes	yes	1638	47.8	11.6
S5	SCI, PS, SMT	yes	yes	no	1472	72.3	8.7
S6	SCI, PS, SMT	yes	yes	yes	2047	61.1	10.3
S7	SCI, PS, FCR, SMT	yes	yes	no	1650	71.6	8.7
S8	SCI, PS, FCR, SMT	yes	yes	yes	2224	60.7	10.3

explains the cash flow increase. This is however only the case when energy shifting from the FTM to BTM partition is permitted, with SCI only contributing marginally to the annual revenues in the remaining scenarios. This is due to the added flexibility through energy trading, which is more closely examined in Section 4.3.

FCR in most cases contribute less to the overall revenue of V2G, as relatively low FCR remuneration prices currently limit profitability. SMT generally being more profitable than FCR is explained by the more volatile price structure as well as the lower requirements compared to providing both positive and negative power over a fixed time window in FCR.

4.2. Added value from EV multi-use and V2G

A general trend that is shown in Table 1 and Fig. 6, is an increase in positive cash flow as more applications are served by the same fleet, with the highest revenues being achieved by bidirectional V2G with all four applications and activated energy shift (scenario *S8*). This however coincides with limited battery lifetimes, due to the increased energy throughput, and thus higher EFCs. This confirms previous findings with stationary battery storage systems [7].

Contrary to stationary storage systems, unidirectional EVs can only charge when connected to the charger. When comparing the scenarios *S1* (unidirectional charging) and *S2* (bidirectional) we show that the annual cash flow increases by 3% when analyzing a fleet with 10 EVs (cf. Table 1). Comparing both scenarios with the reference scenario, it becomes clear that optimized unidirectional charging yields a similar benefit as the bidirectional case, which matches the observation made in [13] that unidirectional smart charging already covers a large portion of V2G potential when grid applications are excluded. When considering FTM applications, such as FCR, V2G capability is a prerequisite for market participation.

There are three clusters to the trend of higher revenues with increasing numbers of applications in *EV multi-use*. Firstly, the scenarios *S1* and *S2* show the lowest cumulative cash flow in comparison to the other optimized scenarios *S3* – *S8*. Secondly, it is observed that the cases *S3*, *S5* and *S7* show an especially defined decrease in battery lifetime. Thirdly, scenarios *S4*, *S6* and *S8* form the cluster with the highest economic increase (cf. Fig. 6). These effects are explained with changes introduced by activating or deactivating energy shift from the FTM to BTM partition, which is more closely examined in the following subsection.

4.3. Shifting energy from FTM to BTM partition

To examine the effect of permitting an energy shift from the FTM to BTM partition for the purpose of driving, the relevant scenario pairs for comparison are *S3/S4*, *S5/S6* and *S7/S8*. In all cases, allowing this energy shift leads to a significant improvement in both generated revenue and battery lifetime. As illustrated in Fig. 5, these revenue increases are largely due to a rise in SCI revenue, which is primarily driven by the combination with the SMT application. This reveals a

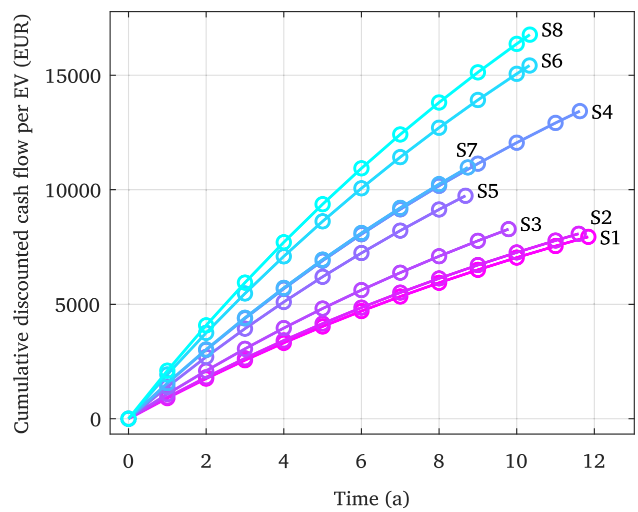

Fig. 6. Discounted cash flow increase per electric vehicle (EV) compared to reference scenario *S0*. Here, the fleet size is 10 EVs and a degradation aware operation strategy is applied.

central advantage of application stacking with permitted energy shift, namely that FTM applications are used to supply energy necessary for mobility provision (cf. Eq. (19)) and guarantee more flexibility for the batteries SOC, without violating preference SOC constraints. In times when FTM electricity costs plus the added charges to shift FTM electricity to BTM partition are cheaper than BTM electricity, charging costs are reduced, which benefits the SCI application. The advantage of multi-use thus arises mainly through added flexibility and the interaction between applications. Based on these results, policy makers that aim to accelerate the electric mobility transition should consider permitting FTM to BTM energy exchange to serve vehicles' mobility needs, for vehicles providing grid services.

Particularly noteworthy here is the SMT application, as this service provides a substantial flexibility increase for the other BTM and FTM applications. Through direct trades during the SMT application, or scheduled transactions during FCR, the application purchases FTM electricity, which is later shifted into the BTM application for mobility purposes. This again reduces the amount of electricity that must be purchased on the BTM side, which increases the profitability of the SCI application significantly. This opportunistic behavior leads to cases where *S4* yields similar cash flows to scenario *S7*, although the latter serves all applications.

It is observed that cases with permitted FTM to BTM shifting, namely *S4*, *S6* and *S8*, experience especially pronounced degradation benefits. This emphasizes the advantages from increased flexibility due to shifting opportunities, which prevents the preemptive behavior of high power charging of the batteries to meet preference SOC requirements in the future. Conclusively, the increased operational flexibility

Table 2
Overview of the analyzed *EV multi-use* scenarios without an active degradation awareness. The cash flow defines the annual cash flow increase in comparison to the reference scenario *S0*. The equivalent full cycles (EFC) define the annual energy throughput. The numbers shown refer to a fleet of 10 EVs.

Scenario	Cash flow (EUR/a)	EFC/a	EOL (a)
S0	0	47.4	7.9
S1	956	47.4	11.8
S2	987	47.5	11.6
S3	1108	149.7	9.2
S4	1634	130.1	10.4
S5	2687	331.6	4.3
S6	3203	313.3	4.3
S7	2819	330.5	4.3
S8	3348	312.6	4.4

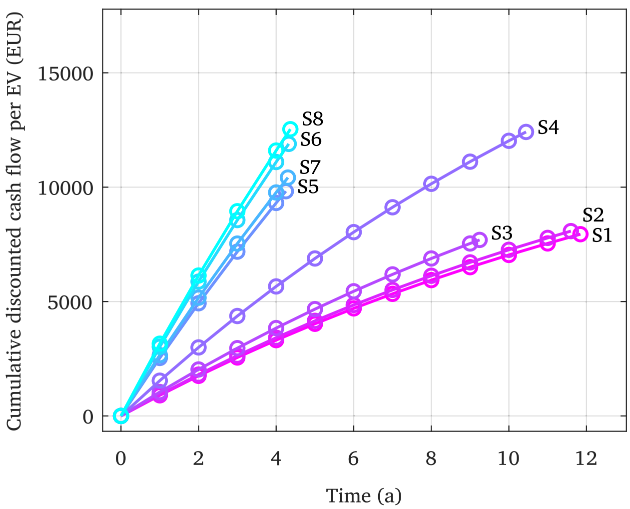

Fig. 7. Discounted cash flow increase per electric vehicle (EV) compared to reference scenario *S0*. Here, the fleet size is 10 EVs and the model does not consider the opportunity costs per cycle when determining the optimal operation strategy.

is not only attractive from a revenue perspective, but also mitigates battery degradation, due to the usage of a broader SOC band and comparatively lower voltage levels [25].

4.4. Neglecting the costs of battery aging

To illustrate the effect of including costs from aging in the optimization, the presented simulations are repeated without degradation awareness. The results of those simulations are shown in Table 2 and Fig. 7.

As visible in the results, the scenarios *S1* and *S2* do not change significantly. This is explained by the fact that the necessary energy throughput of each EV is primarily driven by the mobility service. As more applications are added, however, the revenues of these scenarios increase more steeply, but the overall battery lifetime is significantly reduced. This is especially evident with *S8*, which now reaches 80% of the initial battery capacity after 4.4 years instead of 10.3 years (cf. Tables 1 and 2) but manages to achieve a discounted cash flow of almost 13 000 EUR during the 4.4 year battery lifetime.

The simple charging reference case *S0* reaches its end-of-life after 7.9 years. When introducing optimized charging schemes, overall revenue and in some scenarios even the lifetime is increased. However, neglecting opportunity costs per cycle leads to an even further decrease in lifetime for bidirectional V2G, due to the increased energy throughput. If the optimization is made degradation aware, lifetime is significantly extended for most scenarios or at least maintained. This strengthens previous findings, which emphasized the importance of intelligent charging schemes to extend battery lifetimes [85].

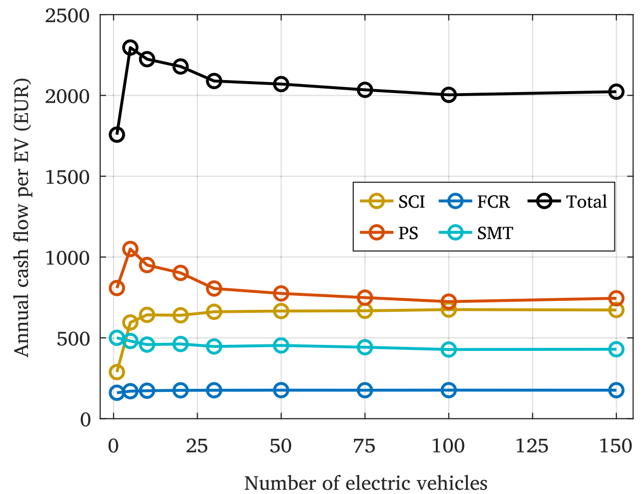

Fig. 8. Annual cash flow contribution per application and electric vehicle (EV) for scenario *S8*. Here, the numbers represent the cash flow increase compared to the reference scenario *S0*.

4.5. Sensitivity analysis on the EV fleet size

A further interesting aspect of *EV multi-use* is its behavior with changing fleet sizes. To examine this, the scenarios are analyzed with increasing numbers of vehicles up to 150 EVs, the results of which are shown in Fig. 8. The annual cash flow initially increases when more vehicles are added, before decreasing again and gradually flattening with rising EV numbers. This behavior is observed with all examined scenarios.

To interpret the reasons for this behavior, Fig. 8 also includes the changes in annual cash flow per served application. While FCR revenues only rise slightly initially and remain mostly constant, SMT shows a declining and later saturating trend, while PS has an initial peak, before showing the same pattern. SCI revenues initially show a large cash flow increase with rising fleet size, before also going into saturation. These observations are primarily driven by the fleets' power and energy demand, as well as the homogeneity of the vehicle usage pattern with growing fleet sizes. When analyzing a fleet with a single vehicle, the optimization has little room for flexibility and is highly dependent on the respective driving profile, which limits the possible cash flow increase. This effect is especially visible with PS, where the timing for charging and existing power peaks are more important. For this reason, adding more vehicles initially leads to an increase in total revenue per EV. As the numbers increase the residual load of the commercial player becomes increasingly defined by the charging power of the vehicle fleet, with fewer opportunities to shift additional power peaks. This leads to the receding annual cash flow from PS in Fig. 8, which settles around an annual cash flow of 740 EUR. As SCI revenues are also defined by the increase compared to the reference charging profile, they initially benefit from the increased flexibility with a growing fleet size. As the fleet size rises, the building's PV generation can be utilized, which contributes to growing SCI revenues, before saturating as the self-generated electricity is consumed for charging the EVs. As more energy can be used to charge the vehicles, less energy from the FTM partition is shifted to the BTM partition, which allows more energy to be purchased and later sold on the spot market, further explaining the slightly higher SMT revenues initially. As the cost for energy shifted from FTM to BTM is subtracted from the SCI application revenue, this also further explains SCI initially benefiting strongly from rising fleet sizes. The FCR cash flows marginally grow at the beginning, which is due to an increase in fleet diversity, which makes power commitments over the necessary FCR provision times more achievable.

5. Conclusions

As electric vehicle market penetration steadily rises it becomes increasingly important to conceptualize intelligent charging schemes to mitigate excessive grid infrastructure stress. Using smart bidirectional charging schemes not only minimizes these negative effects from electric vehicle charging but also provides a diverse set of benefits and economic opportunities. In this context, we analyze grid services for electric vehicles with an emphasis on application stacking to form an *electric vehicle multi-use* concept. For this purpose, a model predictive control framework with an embedded mixed integer linear programming algorithm is developed to evaluate different combinations of vehicle-to-grid based self-consumption increase, peak shaving, spot market trading and frequency containment reserve in the context of a commercial player with an office building and an electric vehicle fleet. This optimization framework is coupled with a semi-empirical battery aging model, to calculate effects on the electric vehicle battery lifetimes. In contrast to previous contributions, this paper focuses on serving multiple applications simultaneously, as well as the separation of storage capacity and power in behind-the-meter and in front-of-the-meter partitions. Furthermore, differences between unidirectional and bidirectional charging as well as effects from front-of-the-meter to behind-the-meter energy shifting, fleet size and aspects regarding degradation modeling are examined.

Based on nine scenarios the results of these simulations show both technical and economic benefits when serving multiple applications simultaneously with electric vehicle fleets. Depending on the served applications, the activation of bidirectional charging and activation of an energy shift between front-of-the-meter and behind-the-meter partitions, an annual cash flow increase between 956 EUR to 2224 EUR per vehicle compared to the simple charging reference case is achieved. The most attractive result is achieved by serving all four applications with the permitted energy shift, which leads to a cumulative discounted cash flow per vehicle of about 17 000 EUR over a lifetime of over 10 years. A clear trend is demonstrated, in which revenue increases as more applications are served and more flexibility through bidirectional charging and front-of-the-meter to behind-the-meter energy shifting is enabled. It is shown that the applications peak shaving and self-consumption increase generate the most revenue, while other applications contribute to achieving more operational flexibility and thus improving overall performance. It is observed that unidirectional smart charging almost reaches the same annual cash flow as bidirectional charging when performing peak shaving and self-consumption increase. Allowing energy to be shifted from the front-of-the-meter to the behind-the-meter partition yields a significant increase in cash flow and battery lifetime, due to the increased flexibility. The optimization is applied with opportunity costs for battery degradation, which are implemented in the objective function. It is thus demonstrated that optimized charging including degradation costs leads to an extension of battery lifetime, while operation strategies without degradation awareness can lead to lifetime reduction of up to 6 years. Finally, it is demonstrated that growing fleet sizes initially coincide with increasing cash flows per vehicle, as more flexibility is enabled. With a fleet size above five vehicles a further increase leads to receding cash flows per vehicle, as more capacity must be allocated to mitigate power costs from the increasing charging peaks. This effect weakens for larger vehicle fleets and the annual cash flow per vehicle saturates at about 100 participating electric vehicles.

For our approach, uncertainties and limitations are considered. Firstly, prediction quality is assumed to be perfect within the rolling horizon and constant annual market prices are assumed over the regarded lifetime. Depending on respective developments in regulation and price structure, especially the latter could change the results both positively and negatively. This paper also operates from the perspective of a fleet operator maximizing revenues and does not consider effects on the grid, such es mitigated power peaks, which could lead to a reduction in societal costs for infrastructure. Furthermore, certain regulatory boundaries are neglected, such as minimum bidding increments, which will require sufficient energy and power capacities. We assume that simultaneous service of front-of-the-meter and behind-the-meter applications is possible, with front-of-the-meter electricity being exempt from taxes and surcharges. In the chosen commercial electric vehicle fleet use case, all vehicles return to one location after route completion; the added complexity of multiple charging locations is an area that can be explored in further research. While this paper makes statements regarding discounted cash flow, a rating of investment attractiveness is not performed. To do this, a calculation of the net present value is necessary, which requires an accurate determination of the financial value of mobility provision, as well as the investment costs.

Further topics for future research could also include additional applications, such as grid congestion management or providing reactive power, as these have been predicted to also be interesting for vehicle-to-grid concepts. Such approaches should emphasize the spatial–temporal flexibility of electric vehicles, as this has implications for infrastructure impact of grid-integrated electric vehicles. Future research can explore additional sensitivity analyses, such as degradation behavior with different fleet sizes and battery end-of-life definitions. Likewise, the presented model can be adjusted to apply to regulatory conditions in additional countries, as the comparison of the effects of different regulatory positions is of interest to policy makers and industry players. Finally, while simulation results make a promising case for *electric vehicle multi-use*, these results remain to be confirmed by field tests.

CRediT authorship contribution statement

Stefan Englberger: Conceptualization, Methodology, Resources, Formal analysis, Validation, Writing. **Kareem Abo Gamra:** Conceptualization, Methodology, Resources, Formal analysis, Validation, Writing. **Benedikt Tepe:** Methodology, Resources, Formal analysis, Validation, Writing. **Michael Schreiber:** Conceptualization, Methodology, Resources, Formal analysis, Validation. **Andreas Jossen:** Supervision, Funding acquisition. **Holger Hesse:** Supervision, Funding acquisition.

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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