TUM School of Engineering and Design

Optimized energy management for battery energy storage via multi-use and multi-storage operation

Stefan Paul Englberger, M.Sc.

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Vorsitzender:		Prof. Dr. Thomas Hamacher
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	2.	Prof. Dr.-Ing. Ulrich Wagner

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Abstract

To curb ongoing global warming, the energy sector must change to increasingly rely on sustainable generation. Due to their volatile nature, and the premise of balancing electricity demand and supply, energy storage plays an important role. In addition to the energy sector, the momentum of electrification is also picking up in the mobility sector, which requires battery storage. While battery storage systems' costs have steadily declined in recent years, too high investment costs still form a considerable barrier to widespread deployment. To boost investment attractiveness, focus can be shifted to maximizing revenues earned in addition to reducing costs. In this thesis, two energy management system concepts are presented and evaluated to maximize the revenue earning potential of stationary and mobile battery storage systems. *Multi-use* aims to simultaneously stack multiple applications on one energy storage system. *Multi-storage* optimizes a network of multiple storages within an energy system. Both approaches modify the energy management system to boost investment attractiveness by exploiting synergies, optimizing power flows and energy throughput. Consequently, utilization rates are enhanced, multiple revenue streams generated, and degradation losses minimized.

Kurzfassung

Um die fortschreitende Klimaerwärmung einzudämmen, muss sich der Energiesektor verändern und verstärkt auf nachhaltige Erzeugung setzen. Durch ihren volatilen Charakter, und die Prämisse, Elektrizitätsnachfrage und -angebot zu balancieren, sind Energiespeicher notwendig. Neben dem Energiesektor nimmt auch im Mobilitätssektor das Moment der Elektrifizierung an Fahrt auf, die ebenfalls Batteriespeicher notwendig macht. Zwar konnte in den letzten Jahren eine kontinuierliche Reduzierung der Kosten für Batteriespeichersysteme beobachtet werden, jedoch gelten die Investitionskosten noch immer als die größte Hürde für den breiten Einsatz dieser Systeme. Um die Investitionsattraktivität zu erhöhen, kann neben der Kostenreduzierung auch die Maximierung der erzielten Erträge in den Fokus rücken. Um das Potential der Einnahmenmaximierung von stationären und mobilen Batteriespeichern zu verbessern, werden in dieser Arbeit zwei Konzepte für das Energiemanagementsystem vorgestellt und bewertet. Das Konzept *Multi-Use* hat das Ziel mehrere Anwendungen simultan mit einem Energiespeicher zu betreiben. Durch die Nutzung von Synergien kann der Nutzungsgrad des Energiespeichers gesteigert und mehrere Einnahmequellen gleichzeitig bedient werden. *Multi-Storage*, das zweite Thema der Arbeit, optimiert ein Netzwerk von mehreren Speichern innerhalb eines Energiesystems. Beide Ansätze modifizieren das Energiemanagementsystem, um die Investitionsattraktivität, durch die Kopplung von Synergien, die Optimierung der Leistungsflüsse und des Energiedurchsatzes, zu erhöhen. Infolgedessen wird der Nutzungsgrad verbessert, mehrere Einnahmeströme generiert und Alterungsverluste minimiert.

Contents

List of publications

Peer-reviewed journal paper contributions (lead author)

a Englberger, S.; Hesse, H.; Kucevic, D.; Jossen, A.: *A techno-economic analysis of vehicle-to-building: Battery degradation and efficiency analysis in the context of coordinated electric vehicle charging*, in: *Energies 12 (5)*, doi: 10.3390/en12050955, 2019

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d Englberger, S.; Abo Gamra, K.; Tepe, B.; Schreiber, M.; Jossen, A.; Hesse, H.: *Electric vehicle multi-use: Optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context*, in: *Applied Energy 304*, doi: 10.1016/j.apenergy.2021.117862, 2021

Self-written sections of peer-reviewed lead author journal paper contributions are partially contained in this doctoral thesis without further reference in the text.

Peer-reviewed conference paper contributions (lead author)

a Englberger, S.; Hesse, H.; Truong, C.N.; Jossen, A.: *Autonomous versus coordinated control of residential energy storage systems – monitoring profit, battery aging, and system efficiency*, in: *Proceedings of IEEE Conference on Sustainable Energy Supply and Energy Storage Systems (NEIS)*, 2018

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f Englberger, S.; Hesse, H.; Jossen, A.: *Cooperative control and economic assessment of residential battery storages in microgrids*, in: *Center for Combined Smart Energy Systems*, Munich, Poster, 2019

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c Almomani, T.; Englberger, S.; Jossen, A.; Witzmann, R.: *Aggregating residential energy storages and electric vehicles through peer-to-peer local energy markets in low voltage distribution grids*, in: *Proceedings of IEEE Conference on Sustainable Energy Supply and Energy Storage Systems (NEIS)*, 2021

Abbreviations

Please note that the list below is based on the main part of this thesis and does not fully cover the abbreviations used in the papers. Each paper itself includes an individual list.

AC . . . . Alternating current

aFRR . . . . . . Automated frequency restoration reserve

BMS . . . . Battery management system

BTM . . . . Behind-the-meter

CAPEX . . . . . Capital expenditure

DAA . . . . Day-ahead auction

DC . . . . Direct current

DSO . . . . Distribution system operator

EFC . . . . Equivalent full cycle

EMS . . . . Energy management system

ENSTO-E . . . . European network of transmission system operators for electricity

EOL . . . . End-of-life

EV . . . . Electric vehicle

FCR . . . . Frequency containment reserve

FTM . . . . Front-of-the-meter

IDA . . . . Intraday auction

IDC . . . . Intraday continuous

IRR . . . . Internal rate of return

LFP . . . . Lithium-iron-phosphate ($LiFePO_4$)

mFRR . . . . . . Manual frequency restoration reserve

MPC . . . . Model predictive control

NMC . . . . Lithium-nickel-cobalt-manganese-oxide ($LiNiCoMnO_2$)

NPV . . . . Net present value

OPEX . . . . . . Operating expense

PI . . . . Profitability index

PS . . . . Peak shaving

PV . . . . Photovoltaic

SCI . . . . Self-consumption increase

SCR . . . . Self-consumption rate

SMT . . . . Spot market trading

SOC . . . . State of charge

SOH . . . . State of health

SSR . . . . Self-sufficiency rate

TMS . . . . Thermal management system

TSO . . . . Transmission system operator

V2B . . . . Vehicle-to-building

V2G . . . . Vehicle-to-grid

V2X . . . . Vehicle-to-X

Symbols

Please note that the list below is based on the main part of this thesis and does not fully cover the symbols used in the papers. A comprehensive list can be found in each individual publication.

A . . . . Weighting of the decision variables in constraints

b . . . . Vector of constants

$\mathbb{C}$ . . . . Cost in EUR

$\mathbf{c}$ . . . . Weighting of the decision variables in objective function

E . . . . Energy in kWh

E^{actual} . . . . . . Actual energy content of energy storage in kWh

$E^{\mathrm{consumption}}$ . . . Energy consumption in kWh

E^{EOL} . . . . . . Energy threshold at end-of-life of energy storage in kWh

E^{nominal} . . . . . Nominal energy content of energy storage in kWh

$E^{\mathrm{production}}$ . . . . Energy production in kWh

E^{purchase} . . . . . Purchased energy in kWh

$E^{\mathrm{remaining}}$ . . . . Remaining usable energy content of energy storage in kWh

$E^{\mathrm{self-consumed}}$ . . Self-consumed energy in kWh

$E^{\mathrm{self-produced}}$ . . Self-produced energy in kWh

E^{sell} . . . . Sold energy in kWh

$E^{\mathrm{throughput,actual}}$. Actual energy throughput of energy storage in kWh

$E^{\mathrm{throughput,max}}$ . . Maximum possible energy throughput of energy storage in kWh

EFC . . . . Equivalent full cycles

EOL . . . . End-of-life

i . . . . Discount rate in %

IRR . . . . Internal rate of return in %

NPV . . . . Net present value in EUR

PI . . . . Profitability index in %

P . . . . Active power in W

$\mathbb{P}$ . . . . Profit in EUR

Q . . . . Reactive power in var

$\mathbb{R}$ . . . . Revenue in EUR

S . . . . Apparent power in VA

SCR . . . . Self-consumption rate in %

SOC . . . . State of charge in %

SOH . . . . State of health in %

SSR . . . . Self-sufficiency rate in %

t . . . . Time in s

$t^{\text{operation,active}}$ . . Active time of storage operation in s

$t^{\text{operation,total}}$ . . . Total time of storage operation in s

τ^{energy} . . . . . . Energy utilization ratio in %

τ^{temporal} . . . . . Temporal utilization ratio in %

$\mathbf{x}$ . . . . Vector of decision variables

1 Introduction

1.1 Motivation and scope of this work

With the undeniable threat of global warming, there is increasing pressure on politics, business, and society to use existing resources efficiently and sustainably [1]. The electricity sector in particular is undergoing a paradigm shift. The increasing number of decentralized energy sources and sector coupling are just two of the driving forces behind this change [1, 2]. To enable the integration of renewable energy [3–5], and the efficient coupling with other sectors, such as the mobility sector, the demand for energy storage systems is growing [6, 7]. Through the continuous increase of renewable energy supply and expected global rise in electricity demand of 20 % over the coming decade, the technical stress on power grids is also growing [8].

To follow these trends and ensure the security and quality of electricity provision, flexibility is the cornerstone of future energy systems. Flexibility entails reacting as swiftly and reliably as possible to the changing conditions of the energy system, a task that energy storage systems are predestined to fulfill [9]. Nevertheless, even in the rapidly growing market for energy storage systems, there are setbacks at the global level. In 2019, for example, global annual energy deployments declined for the first time in the decade [10]. In addition, the onset of the Covid-19 pandemic has put additional stress on the supply chain and logistics of battery cell manufacturers, which has further hampered this complex market's growth [11]. Despite these setbacks and risks, the annual installed capacity of utility-scale battery storage systems is expected to increase from about 25 GW in 2020 to over 100 GW in 2030 [8].

In the energy storage market, a distinction is made between stationary and mobile energy storage systems. By 2030, the combined market for energy storage is expected to grow by 2.5 to 4 TWh per year [12, 13]. Due to political incentives and continuous cost reductions [12–14], mobile energy storage in electric vehicles (EVs) is one of the dominant drivers for storage deployment. With 160 GWh of automotive batteries produced in 2020, lithium-ion is the leading technology for mobile energy storage systems [12]. For stationary energy storage there are several established technology types. Thermal (e.g. chilled water thermal storage, molten salt thermal storage), mechanical (e.g. pumped hydro storage, flywheel), electric (e.g. capacitor, inductor), chemical (e.g. hydrogen storage), and electro-chemical (e.g. battery) storage technologies are differentiated [15–17]. Although mechanical storage systems, particularly pumped hydro storage, accounted for 96 % of total installed storage capacity and thus the largest technology type for stationary systems in 2017 [15], battery energy storage systems are the fastest growing category [12, 13]. Lithium-ion technology already accounted for 59 % of global electro-chemical storage power capacity in 2017, with lead-acid and sodium-based battery systems constituting the other larger categories [15]. Due to the increasing demand, the annual global deployment of stationary storage (excluding pumped hydro storage) is expected to grow at a compound annual growth rate of up to 27 % until 2030 [13].

The broadening repertoire of applications for battery energy storage systems has further driven their deployment [15, 18]. The increased demand for efficient and durable energy storage systems has favored lithium-ion technology, particularly in recent years [10]. Rising expertise, learning curve effects [19, 20], and economies of scale have led to a continuous reduction in battery system costs [21–23]. In addition to the technical achievements, demand-pull policies and the resulting deployment increase has further grown battery systems' investment attractiveness [20, 24]. Although a decline in the cost of battery storage systems has been observed and is expected to continue due to the above-mentioned trends [19], the investment requirement is still classified, in the literature, as the most significant barrier to energy storage deployment [24–26]. Due to the economic relationship between profit, revenue, and costs, both reducing costs and increasing revenues has a positive influence on the investment attractiveness of energy storage [15, 27, 28]. To yield the highest possible revenue for an energy storage system, the most lucrative applications should be served first [18, 29]. To also ensure the reliable operation of applications, the storage system should be tailored to serve the selected application [30]. The decisive factor for generating revenue for an energy storage system is the operation strategy [31–33]. This defines how a storage facility behaves based on the conditions in the energy system. The energy system is defined as a delimited technical unit in which the power flows are optimized to achieve a desired goal. Such an energy system can be, for example, a household with photovoltaic (PV) generator, electricity demand, stationary energy storage, and EV.

For the successful implementation of an operation strategy, there are several components required. In a lithium-ion battery, several battery cells are interconnected to form modules and increase its capacity (parallel connection) and voltage level (series connection). These modules are then combined to form a battery storage system. To connect an energy storage system to an alternating current (AC) grid, the direct current (DC) power of the battery cells is converted using inverters that are installed in the power electronics [34]. Depending on the AC voltage level and topology of the storage system, it may be necessary to also add converters or transformers to the power electronics. It may be necessary to install electricity meters in the energy system to comply with regulatory requirements. To ensure that the energy storage system operates in the physically optimal ranges, monitoring systems are essential. For instance, the battery management system (BMS) continuously monitors the battery cell states, such as voltage and current [35, 36]. Since fault currents and over-voltages can lead to excessive storage degradation and, in the worst case, to safety-critical conditions, the BMS is generally integrated on the storage device [37]. Another component of the monitoring system is the thermal management system (TMS) [38, 39]. This continuously monitors the temperature in the storage system, checks compliance with defined temperature windows, and can activate cooling processes if they are available [40].

The central component for the efficient operation of an energy storage system is its energy management system (EMS). This monitoring system collects the states of the energy system and processes them into the operation strategy. The task of the operation strategy is to calculate the best possible deployment strategy for the energy storage system, based on the system states and forecast values. Recently, it has been shown that especially the prediction and optimization of the EMS plays an increasingly important role [41–43]. As described in greater detail in this thesis, the complexity of the EMS increases depending on the use case.

In the work presented here, the methods of *multi-use* and *multi-storage* for stationary and mobile energy storage systems are evaluated.

The *multi-use* method describes the stacking of applications on an energy storage system. By serving multiple applications simultaneously, synergies can be exploited, and the investment attractiveness of the storage system is maximized. Since both energy and power are required when serving applications, the EMS must successfully distribute the corresponding storage capacities among the applications. The remainder of the thesis delves deeper into what is needed for a successful implementation of *multi-use*, highlighting its types, advantages, and challenges. With the use of a newly designed optimization algorithm, the concept of *multi-use* for large-scale stationary storage systems and EVs is analyzed.

The *multi-storage* method focuses on the interconnection between energy storage systems. Generally, individual energy storage systems are each equipped with their own EMS. Conflicts can arise when multiple energy storage systems, with respective EMSs, are integrated into one energy system. Thus, the *multi-storage* concept tackles this issue by applying a common EMS to multiple energy storage systems, allowing the simultaneous operation under one objective function. This method enables the use of synergies between participating storage systems and the energy system as a whole, to effectively allocate power and maximize flexibility potential.

Since the optimization of the EMS is the focus of this work, several optimization algorithms are presented and compared with state-of-the-art approaches. In addition to the use of linear programming and mixed-integer linear programming algorithms, the work also deals with prediction methods. A model-predictive control approach is developed, which allows the use of forecast data and calculates optimized control signals to the energy storage based on these forecasts. By coupling optimization algorithms and semi-empirical degradation models, an optimized operation strategy of the EMS can be calculated, which allows the increase of revenue streams and simultaneous limitation of degradation losses.

1.2 Thesis outline

In this publication-based dissertation, four previously published papers are addressed and built upon. The presented work is divided into seven chapters – the structure and interrelationships of which are shown in Figure 1.1.

To provide the context for the work as a whole, Chapter 2 highlights the methods used in the presented publications and discusses them based on existing literature. In addition to the reference to state-of-the-art research on the energy management for battery storage systems, the chapter introduces key performance indicators and metrics used in the following chapters.

In Chapter 3, the first paper with the title *A techno-economic analysis of vehicle-to-building: Battery degradation and efficiency analysis in the context of coordinated electric vehicle charging* is presented [44]. The paper introduces the *multi-storage* method entailing both stationary and mobile energy storage systems for a single prosumer household.

Building on the results at a household level, Chapter 4 extends the *multi-storage* method to the community level. In the publication, *Evaluating the interdependency between peer-to-peer networks and energy storages: A techno-economic proof for prosumers*, the flexibility provision in a local electricity market is analyzed empirically, using both home energy storage and EVs [45].

Chapter 5 consists of the third presented article, with the title *Unlocking the potential of battery storage with the dynamic stacking of multiple applications* [46]. Based on a large-scale stationary storage system, the designed *multi-use* methodology is evaluated using four well-established energy storage applications.

Extending the *multi-use* method for stationary storage systems, Chapter 6 introduces a *multi-use* operation strategy for EV fleets. The publication, titled *Electric vehicle multi-use: Optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context* [47], entails both a *multi-use* and a *multi-storage* character, as its method optimizes the power flows to the applications as well as the power flows for multiple storage systems.

Finally, Chapter 7 presents a cross-thematic discussion section with reflections on the previous chapters. This chapter also summarizes the key findings of the study and highlights further areas of research.

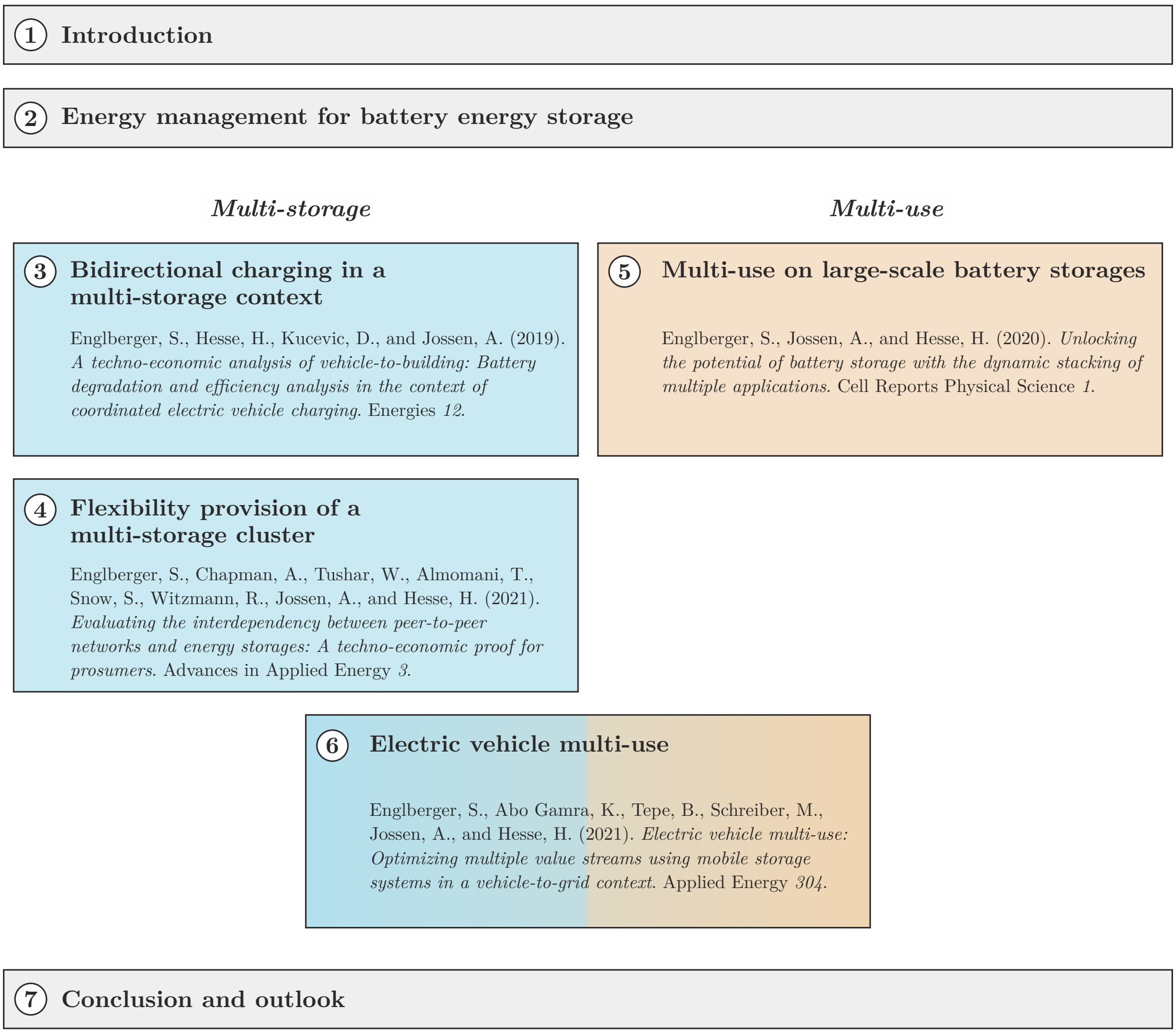

Figure 1.1: Graphical structure of this thesis, highlighting the seven chapters.

2 Energy management for battery energy storage

The following chapter provides a summary of existing literature in the field of energy management and energy storage systems. It also serves as a basis for the other chapters and defines the most important performance indicators of this work. Although the respective papers of the subsequent chapters present the designed methods in detail, this chapter introduces the context of these methods and discusses them with existing literature.

In Section 2.1, key metrics are defined and explained. Building on the metrics, Section 2.2 presents relevant applications and revenue sources for battery energy storage systems. Section 2.3 explains the context of *multi-use* for stationary and mobile energy storage systems. The topic of *multi-storage* operation is presented in Section 2.4. Finally, Section 2.5 highlights the optimization of EMSs and discusses their implementation.

2.1 Definitions

To implement methods shown in this work, several technical and economic definitions are introduced, some of which are already established in existing literature. Undoubtedly, an abundance of terms and metrics find use in the field of lithium-ion batteries; nevertheless, the most significant definitions are highlighted in this section.

End-of-life and state of health Due to the limited lifetime of energy storage systems, it makes sense from both a technical and economic perspective to define the usable lifetime or the occurrence of the end-of-life (EOL) [48]. Here, the EOL corresponds to the state at which the battery characteristics meet defined thresholds [49]. Usually, the remaining battery capacity or the internal resistance is used to calculate the limits for lithium-ion batteries' EOL [50, 51]. As it will be described in more detail in Section 2.5.5, degradation processes in the cell lead to a decrease in the usable cell capacity [52, 53]. The internal processes lead to an increase in internal resistance, which causes rising losses in the cell. Since the usable capacity is of particular significance, literature and this work refer to the EOL definition by means of the capacity. Although the term, battery capacity, is primarily used to refer to the charge capacity of a battery cell, in this work it refers to the storage system's energy capacity. Thus, the EOL state of a battery cell occurs when its remaining capacity $E^{\text{remaining}}$ declines and reaches the defined threshold E^{EOL} (cf. Equation 2.1).

$$\text{EOL} := E_t^{\text{remaining}} = E^{\text{EOL}} \tag{2.1}$$

Closely related to the EOL of a lithium-ion battery is its state of health (SOH) [54]. This term quantifies how far the aging process has progressed based on the battery capacity. The SOH is most commonly defined as the ratio of remaining and nominal battery capacity, as seen in Equation 2.2. The alternative definition, shown in Equations 2.2 and 2.3, denotes that the SOH equals 0 % when the EOL threshold is reached [55]. These different definitions can lead to highly disparate SOH values. For instance, assuming a remaining capacity of 90 % and an EOL threshold of 80 % of the nominal capacity, respectively, then the resulting SOH values for Equations 2.2 and 2.3 are 90 % and 50 %. The former definition, also the more widespread one, is utilized in this work.

$$\mathrm{SOH}_t = \frac{E_t^{\mathrm{remaining}}}{E^{\mathrm{nominal}}} \tag{2.2}$$

$$\mathrm{SOH}_t^* = \frac{E_t^{\mathrm{remaining}} - E^{\mathrm{EOL}}}{E^{\mathrm{nominal}} - E^{\mathrm{EOL}}} \tag{2.3}$$

State of charge As with the definition of the SOH, the state of charge (SOC) is also based on energy-related values (cf. Equation 2.4). Therefore, the SOC describes the proportion of the actual energy content in the battery in relation to the remaining energy content, which is the nominal energy content of the battery reduced by degradation processes. With the consideration of the capacity fade, one can infer the open-circuit voltage of the battery based on the SOC [56].

$$\mathrm{SOC}_t = \frac{E_t^{\mathrm{actual}}}{E_t^{\mathrm{remaining}}} \tag{2.4}$$

Energy throughput A decisive component in finding an optimal operating strategy for an energy storage system is the energy throughput. In literature, the definition of the equivalent full cycle (EFC) acts as its quantitative value. The EFC determines the number of charge and discharge cycles through the energy storage [57]. A full cycle consists of the sum of one charge and one discharge cycle. Due to the definition that the energy throughput is related to the nominal storage capacity, this quantity is independent of degradation processes. In addition to the determination of the EFC, other designations can be found in literature, such as the full equivalent cycle or full cycle equivalent [57–59].

$$\begin{aligned} \mathrm{EFC}_t &= \frac{|E_t^{\mathrm{actual}} - E_{t-1}^{\mathrm{actual}}|}{2 \cdot E^{\mathrm{nominal}}} \\ &= \frac{|\mathrm{SOC}_t - \mathrm{SOC}_{t-1}|}{2} \cdot \mathrm{SOH}_t \end{aligned} \tag{2.5}$$

With this formulation, efficiency losses during charging and discharging are neglected, as for the energy throughput through the cell only the net-charge and net-discharge energy is considered. Since a used cell requires a greater change in SOC for the same energy extraction than a new cell (different $E^{\mathrm{remaining}}$), this leads to an overestimation, which needs to be corrected by including the SOH in the EFC calculation (cf. Equation 2.5).

Revenue, Costs, and Profit Profit describes the difference between revenue earned and costs incurred (cf. Equation 2.6). In the context of energy storage systems, revenues are generated by serving applications [15]. These applications produce value add either by generating revenues in markets or by reducing opportunity costs. To fully evaluate an energy storage system and to dimension it in an economically reasonable way, all costs must be included in the calculation. Therefore, costs can be differentiated into capital expenditures (CAPEX) and operating expenses (OPEX). CAPEX describe the investment costs for the acquisition or investment of the asset and OPEX, include the ongoing costs for the operation, maintenance, and servicing of the asset.

$$\mathbb{P}_t = \mathbb{R}_t - \mathbb{C}_t \tag{2.6}$$

In addition to valuation by profit, the metric of cash flow is also useful for the valuation of investments [60]. In accounting, revenue can be earned, and costs incurred without actual payments being made. Thus, profit is generally detached from the actual cash in- and outflows by a time delay. In this thesis, the term profit and cash flows are used synonymously, as the time periods for both metrics are defined identically, unless otherwise stated.

Net present value To compare multiple investment options and obtain a consistent metric for decision-making, net present value (NPV) is commonly used. NPV, by definition, considers all cash flows until the investment's termination, including the cost of capital required, and is a widely used metric in investment management. Typically, for the NPV method, cash flows are broken down and evaluated on an annual basis. Both expected cash inflows and the initial investment costs (cash outflow) are included in the calculation. In Equation 2.7 the investment costs ($\mathbb{C}^{\text{invest}}$) can be understood as the assets' CAPEX. For energy storage systems, CAPEX describe the acquisition costs for the energy storage system, i.e. the costs for the storage unit in the form of cells and modules, and also the costs for necessary peripheral equipment such as power electronics and thermal management. To account for the future cost of capital, the cash flows must be depreciated. This depreciation takes place by adjusting cash flows with the discount rate i, which represents the return that could be earned from alternative investments. Thus, the time value of money is considered. In Equation 2.7 the profit, $\mathbb{P}_n$, describes the net cash flow at time period n. With the definition that cash flows are depreciated annually, this process is repeated and accumulated until the expected end of investment. In this work, the end of the investment period is assumed to equal the technical EOL of the energy storage system. In practice, after the technical EOL, the storage system can be either recycled or utilized in a second life use case [61]. In the former, this would result in additional costs and in the latter, revenues to be added to Equation 2.7, which are neglected in this work.

$$\text{NPV}_{\text{EOL}} = -\mathbb{C}^{\text{invest}} + \sum_{n=1}^{\text{EOL}} \frac{\mathbb{P}_n}{(1+i)^n} \tag{2.7}$$

As a result, the NPV provides an absolute value of the investment for the present time in a chosen currency and can be used to recommend or discourage an investment. For instance, if the NPV of a project is negative, it is advisable to choose an alternative investment. When comparing investments' NPVs, the investment with the highest NPV will likely be the most profitable.

A similar method to the NPV is offered by the internal rate of return (IRR). Following the definition of NPV, the IRR describes the discount rate at which the NPV becomes equal to zero (cf. Equation 2.8). Although this is a simple approach to determine the upper bound of the discount rate to allow for a positive investment, the NPV offers the possibility to consider varying discount rates for the different time periods n.

$$0 = \mathrm{NPV}_{\mathrm{EOL}} = -\mathbb{C}^{\mathrm{invest}} + \sum_{n=1}^{\mathrm{EOL}} \frac{\mathbb{P}_n}{(1+\mathrm{IRR})^n} \tag{2.8}$$

Profitability index By definition, the NPV approach allows investments to be compared that have a similar investment volume. If investment options with different investment costs and strongly differing cash flows should be compared, it is recommended to use relative metrics, such as the profitability index (PI). As shown in the definition in Equation 2.9, the NPV is divided by the investment costs to calculate the PI. Like the NPV, the resulting value has no lower or upper bound, however, the value should not drop below -1, since this would mean that the net cash flows of the investment are negative. For the further interpretation of the PI, a PI of zero means that the investment is NPV neutral. As for the NPV, the option with the highest PI should be preferred when comparing investments.

$$\mathrm{PI}_t = \frac{\mathrm{NPV}_t}{\mathbb{C}^{\mathrm{invest}}} \tag{2.9}$$

2.2 Energy storage applications

Energy storage applications constitute the serving of markets and the yielding of revenue streams with an energy storage [62]. As a rule, these applications are designed to motivate the storage operator to participate in the market [31]. For both stationary and mobile energy storage, there is a variety of available revenue streams, which are explained in more detail below. In the following chapters, the techno-economic analyses focus on the applications self-consumption increase, peak shaving, frequency regulation, spot market trading, and mobility provision. However, since there are many other sources of value add for energy storage, particularly battery energy storage systems, additional relevant applications are presented in this section.

As in most sectors, the value chain in the electricity sector can be divided into several parts. First, electricity is generated by electricity producers. Secondly, transmission system operators (TSOs), followed by distribution system operators (DSOs) ensure the electricity supply is transported to consumers. These consumers include both private individuals and commercial customers, who differ in terms of their purchased electricity volumes. Energy storage can be installed and operated across the whole electricity value chain, but from a regulatory perspective it is important to ensure that unbundling laws are satisfied [29]. In the applications discussed, the focus is on revenue streams that can be served by an electricity consumer. To comply with the mentioned unbundling laws, a distinction is made between behind-the-meter (BTM) and in front-of-the-meter (FTM) applications.

Behind-the-meter applications Behind-the-meter applications influence the electricity flows at the grid connection point that are behind the electricity meter; and thus, have a consumer-oriented character [63, 64]. Depending on the point in the electricity value chain and the voltage level, taxes and charges are added [65, 66]. For German electricity consumers these price components include: procurement and distribution, grid charge and metering, value-added tax, concession fee, EEG (German renewable energies act, German: Erneuerbare-Energien-Gesetz) surcharge, KWKG surcharge, §19 StromNEV levy, offshore grid levy, levy for interruptible loads, and electricity tax [67, 68].

Depending on the volume of electricity purchased and the type of consumer (household or commercial customer), the amount of the cost components can change [67, 68]. Since all levies and taxes must be paid for BTM electricity, the focus here is on ensuring the most favorable possible purchase and sale conditions [69].

Front-of-the-meter applications Compared to BTM, FTM applications affect the electricity flows in front of the electricity meter (e.g. at the grid connection point) [63, 70]. There is no consumption characteristic in FTM applications, only a withdrawal and temporary storage of energy [46, 47]. In the case of FTM energy, the points of grid efficiency and system efficiency are in the foreground [63]. Grid efficiency is the reduction of stress on the grid, such as the balancing of power peaks in the distribution grid. An established application in the area of system efficiency is frequency regulation, which is intended to balance the energy fed into and drawn from the grid to stabilize the grid frequency. Due to the grid- and system-serving character of FTM applications, the electricity costs for exchanged energy are subject to favorable conditions [46].

Self-consumption increase This BTM application focuses on the use of self-generated energy. With the falling prices for renewable energy sources, such as PV generators [71], interest in the self-consumption increase (SCI) application is also on the rise [72]. Both private households and commercial electricity consumers try to use the electricity from their generation units to cover their own consumption [73, 74]. This is incentivized by the difference between the electricity purchase and sales price [24]. In the case of Germany, there are still higher remuneration prices due to the EEG subsidy [75], but these are declining. In the case of non-subsidized, or post-EEG, generators, the economic incentive is strengthened as the price difference is even greater [76].

The example of PV generators shows that the direct use of self-generated electricity is only possible at times when the generating unit provides electricity [77, 78]. To further increase the use of self-generated energy, excess generation can be stored to be withdrawn during times of higher consumption [79, 80]. This enables self-generated energy to be used behind-the-meter at times when there is no electricity from the generation unit [81, 82]. To quantify this approach, the metrics self-consumption rate (SCR) and self-sufficiency rate (SSR) are used to indicate the proportion of self-generated or self-used electricity (cf. Equations 2.10 and 2.11) [44, 83]. Here, $E^{\mathrm{self-produced}}$ represents the energy from the generating unit to the consumption and/or storage units, whereas $E^{\mathrm{self-consumed}}$ denotes the flow from generating unit and/or previously stored energy from the generating unit to the consumption. $E^{\mathrm{production}}$ and $E^{\mathrm{consumption}}$ denote the power flows from the generators and to the loads respectively.

$$\mathrm{SCR}_t = \frac{E_t^{\mathrm{self-produced}}}{E_t^{\mathrm{production}}} = 1 - \frac{E_t^{\mathrm{sell}}}{E_t^{\mathrm{production}}} \tag{2.10}$$

$$\mathrm{SSR}_t = \frac{E_t^{\mathrm{self-consumed}}}{E_t^{\mathrm{consumption}}} = 1 - \frac{E_t^{\mathrm{purchase}}}{E_t^{\mathrm{consumption}}} \tag{2.11}$$

The SCI application allows the reduction of electricity costs, since more self-produced electricity is used and thus less electricity needs to be purchased [24]. An energy storage system investment can be economically lucrative if the avoided costs due to SCI exceed the investment costs [78]. Due to the energy storage's high energy throughput and partially high C-rate, special care must be taken here on degradation and efficiency losses [58].

Peak shaving Peak shaving, defined as a BTM application in this work, describes the act of reducing load peaks to minimize demand charges. As described in the SCI application, electricity tariffs may differ between households and commercial electricity consumers [67, 68]. In Germany the separation is made at a limit of 100 MWh annual electricity demand [84]. If a consumer is above this value, a power-related price in addition to the energy-related electricity price is charged. The amount of this power-related price depends on the consumer's reference hours of use [84]. The number of hours of use is calculated by dividing the energy drawn from the grid by the maximum peak power in the specified period [66]. Approximately, the lower the number of hours of use are, the higher the power-related share of the electricity tariff will be. The power-related costs are the product of the power-related price and the maximum power peak of the demanded electricity from the grid. For the electricity costs, the energy drawn is multiplied by the energy-related tariff and added to the power-related costs.

The aim of the peak shaving (PS) application is to shave high power peaks [85, 86]. From a regulatory perspective, it is sufficient to consider 15-minute average values, as these are the ones measured [84]. For an electricity consumer, there are three ways to avoid excessively high power peaks [87]. First, demand-side management can be used to curtail or shut down the machines and processes that are causing the high demand [88]. Since this requires intervention in potentially critical production processes, there is also the option of connecting available generation units such as PV generators, the so called supply-side management [89]. If such units are not available or do not supply electricity, there is the third option of installing energy storage.

For this application, the energy storage unit serves as a source of energy to reduce the demand from the grid and cover the power peak. Since the energy storage unit must store energy for this task, its SOC decreases and therefore the storage unit has to be recharged at times when there are no power peaks [58]. For this purpose, the operation strategy must ensure that no power peaks are created when charging the storage. The PS threshold defines the power value that is still okay to draw power from the grid. If the demand is above the threshold, the storage is activated, and excess energy is discharged [46].

In Germany, there are both annual and monthly tariffs that define the power-related price [84]. Within the defined annual or monthly billing period, the maximum value of the power demand is the main factor. Since demand usually has a fluctuating profile, individual, very high power peaks are particularly lucrative to shave [90]. As shaving at smaller thresholds can lead to disproportional high energy throughput and thus increased storage aging [91, 92], knowledge of the consumption or load profile is crucial [93]. Simple rule-based PS operating strategies are applied in a way that the SOC of the storage is constantly kept as high as possible [58, 85]. If it occurs that the reference power is above the threshold, the storage is discharged and the SOC decreases. As a result, the high SOC ensures that the potential for the PS application is high but brings the disadvantage that the battery cell degradation is accelerated (cf. Section 2.5.5) [58]. This again motivates for an efficient prediction of the load profile and the optimal choice of the PS threshold [46, 94]. With the mentioned operation strategy and the volatile behavior of load profiles, it becomes clear that the time utilization of the storage is relatively low [34], which in turn makes the stacking of applications especially interesting (cf. Section 2.3) [95, 96].

As with SCI, the profit generated by the PS application is actually a reduction in costs. By shaving high power peaks, the leverage of the power-related price decreases and thus the electricity costs are reduced. This is incentivized by the fact that the DSO has less power peaks occurring, which results in lower losses and reduced grid burden [77, 97]. Depending on the grid level at which the grid connection point is installed, the power-related price can also vary. Although it is conceivable that energy storage systems could also be installed on the FTM side by the DSO, it is still legally difficult to determine whether this is in line with unbundling laws [29, 90]. For the rest of this work, the PS application is always associated with BTM.

Frequency regulation Frequency regulation is a FTM application with the task to balance the grid frequency around its norm value. Electricity grids do not recognize national borders but follow physical laws and allow electricity to be traded between countries. Germany lies within the continental Europe synchronous area, which is managed by the European association for the cooperation of transmission system operators for electricity (ENTSO-E) [98]. This AC grid area is characterized by a nominal frequency of 50 Hz. The constantly fluctuating feed-in and feed-out processes in the large grid area cause fluctuations in the grid frequency [99]. A drop in frequency indicates that an accordingly high load or electricity demand, is being drawn from the grid. The nominal grid frequency can only be reached when feed-in and consumption are balanced again. Frequency regulation serves this purpose of grid balancing [100]. In the ENTSO-E area, there are three products that are used for system security and to ensure that the grid frequency does not deviate too far from the nominal frequency: frequency containment reserve (FCR) [101–103], automatic frequency restoration reserve (aFRR), and manual frequency restoration reserve (mFRR) [104–107].

All three products have the same motivation and mechanics: If the frequency is below the nominal frequency, electricity is fed into the system; if the frequency is higher, loads are activated that draw excess electricity from the grid [108]. The difference between the three products is the time of activation. In the case of a frequency deviation, the FCR is the first product that must be activated at full power within 30 seconds [109, 110]. In the case of longer lasting frequency deviations, FCR provides its power for up to 15 minutes. In the meantime, the aFRR is activated no later than 5 minutes post-error and provides power for up to 15 minutes. If the frequency is still not corrected after 15 minutes, the mFRR is activated, which in turn provides its power for up to 60 minutes [98, 108]. If, despite the provision of FCR, aFRR, and mFRR, the frequency deviation still cannot be resolved, interruptible loads are the last alternative before the grid collapses [111]. Since battery storage is predestined for the economically lucrative FCR application due to its quick response times [9, 63, 112], the remainder of this work will focus on FCR.

As an established market and FTM application overseen by the TSOs, there are certain requirements and regulations that participants must comply with. To manage the number of participants in the market and avoid very small bids, the FCR product is offered in MW increments [58, 108]. Unlike the aFRR and mFRR, the FCR is a symmetrical product. This means that the power offered and awarded must be provided in both positive and negative directions, identified as FCR (POS/NEG). The positive power corresponds to energy supplied to the grid (discharge of energy storage). The FCR application's market – in its present form – was initially launched in 2007. It started with monthly delivery periods, but this period has shortened steadily to weekly, daily, and to the currently applicable 4 h [46, 108]. For the participants in the market, this means that they can apply for six time slots every day. Besides the offer period, also the bidding process has changed in recent years [111]. Here, the pay-as-bid procedure was in place until the first half of 2019 and was replaced by marginal pricing. Since July 2019, the bids are collected until the tender closing date. The bids are then sorted by ascending bid price. The highest price, which is still within the total required FCR power for the corresponding 4 h time period, defines the price for all participants.

To successfully operate a prequalified technical unit, such as a battery energy storage, in the FCR application, it must act in a frequency-controlled manner. This means that the energy storage unit must absorb or release energy in the event of a locally measured frequency deviation [108]. Since the electrical grid shows a continuous frequency change, the range ± 10 mHz is referred to as the dead band. Within this range around the nominal grid frequency, an energy storage device does not have to, but can supply or absorb energy. If there is a larger frequency deviation, the energy storage needs to intervene. Depending on the frequency, the control power is provided linearly to the frequency deviation. In the extreme case of a deviation of 200 mHz or more, the total offered power should be provided. The relationship between 50 Hz nominal frequency and 200 mHz maximum deviation results in a static of 0.4 % in the FCR product [108].

To provide additional security, each prequalified technical unit needs to always maintain an energy buffer of 15 minutes. In addition, it must also ensure that the technical capacity of the unit is 25 % higher than the FCR capacity offered [46, 47]. This should give the participant the opportunity to carry out scheduled transactions on spot markets to adjust its operating point [113]. In addition to the scheduled transactions, there are other degrees of freedom that make it possible to optimize the operation of energy storage units in the FCR application [114].

Spot market trading Spot market trading is a FTM application that utilizes price spreads on the wholesale electricity market to realize arbitrage opportunities. Spot markets are defined as economic locations where trading objects, such as commodities are traded with the help of standardized contracts [115]. Since there is also a continuous interplay of supply and demand for electricity, a distinction is made between three electricity spot markets in Germany: intraday-continuous (IDC), intraday auction (IDA), and day-ahead auction (DAA) [46, 116]. The three spot markets differ in terms of trading times and delivery periods. On the DAA market, bids are accepted until 12 noon of the previous day, and a delivery period of one hour applies [117, 118]. The IDA's 15-minute trading blocks can be submitted until 3 p.m. the day before delivery [119–121]. In contrast, the IDC market also trades 15-minute trading blocks, but trading opens at 3 p.m. the day before delivery [119, 122]. The focus of further work is on the IDC market, as it usually has the highest fluctuations and price spreads [123], and battery storage systems are characterized by their fast response times [9].

When participating in spot markets with battery storage, the aim is to buy energy at low prices and sell it later when market prices are higher. The process of utilizing the price difference in this way is also known as arbitrage trading [124]. To optimize the operation of energy storage systems at the IDC, the efficiency of the energy storage system during the charging and discharging process, in addition to the market prices, is of decisive importance [122, 125]. The more volatile the price signal, the more opportunities there are for the EMS to trigger trades [47]. More trades, in turn, mean that energy throughput increases, illustrating the strong influence of energy efficiency and battery degradation.

As with other established FTM markets and applications for energy storage, there are also regularities that must be met in spot market trading. The requirements, defined by the European energy exchange, include that the power of the 15-minute trading signals must be at least 100 kW [46, 116]. As shown in existing publications, spot markets can also be served simultaneously [126, 127]. This can again increase the economic result, though here the added value is generated not only by the energy storage but also by using synergies of the different markets. Since this thesis deals with the behavior and the added value of the energy storage system, markets are considered exclusively. Since the operation strategy of the EMS is in the foreground, it is also assumed that every trading transaction involves a physical delivery [46, 47]. This has the effect that electricity can be bought or sold exclusively at each trading period. To generate representative results, the simulations and optimizations shown are based on historical price signals from the IDC market in Germany [116, 128]. These price signals generally consist of different components such as the weighted average price signal, which is weighted on the trading volume. In addition, the high and low signals, which reflect the highest and lowest market prices, respectively, are also used. The extent to which these price signals have been incorporated is indicated in the relevant publications in Chapters 5 and 6.

Mobility provision and V2X Mobility provision is also classified as a BTM application due to its consuming characteristic [47]. The focus here is on the provision of energy from the battery of an EV to the electric motor to move the vehicle. Compared to other applications shown, it is difficult to establish a target function with the economic added value for this application, since each user estimates and quantifies the added value of driving differently. Rather, this application is like a constraint that must always be adhered to [129, 130]. This constraint must guarantee that enough energy is stored in the vehicle's battery at any given time so that future journeys can be carried out without any limitations until the next recharge. In addition, previous literature has highlighted that due to the range anxiety effect, a certain energy buffer should always be held in reserve [131].

Since passenger vehicles spend about 96 % of their time parked [132], it is a good opportunity to use the energy storage of EVs for additional applications. To provide more services with the storage, the EMS needs to be able to modify the charging strategy of the EV. Smart charging strategies make it possible to optimize the charging power to achieve the desired result [133]. Compared to stationary energy storage, EVs, besides the fact that they are not always connected to the grid, usually have the characteristic that they can be charged only unidirectionally. With the steadily increasing energy content of mobile energy storage systems in passenger vehicles, there is growing interest in research and industry to be able to discharge the large energy storage systems into the electricity grid in a targeted manner. The technology that enables this behavior of EVs and respective chargers is known as bidirectional charging or vehicle-to-X (V2X) technology [129, 134, 135]. The term V2X covers a range of technologies that have in common that energy flows from the vehicle's battery to other technical entities. Representatives of the V2X group include: vehicle-to-vehicle (V2V) [136], vehicle-to-building (V2B) [44, 137], vehicle-to-home (V2H) [138], and vehicle-to-grid (V2G) [139–143].

Reactive power provision Within AC systems, the relationship of the phase shift angle between current and voltage, as well as the formula $S^2 = P^2 + Q^2$, explains the apparent power S, where P is the active and Q is the reactive power. If the phase shift between current and voltage is not equal to zero, then reactive power is occurring. The presence of reactive power also affects the electricity grid and can lead to voltage deviations [144]. Depending on the state of the grid, either capacitive or inductive reactive power can be used to counteract voltage deviations and allow the effective transmission of active power [145]. In the past, conventional power plants were also responsible for providing reactive power. As the energy transition progresses, these conventional power plants are increasingly being replaced by renewable energies. By equipping energy storage systems with suitable power electronics, it is possible to provide reactive power to the grid. The central unit for the provision of reactive power is the inverter, which provides inductive and capacitive reactive power depending on its power factor [146]. From an economic point of view, the provision or compensation of reactive power is not yet standardized in Germany. Although there are guidelines that foster its operation, it is up to each DSO how the economic incentive is established [147, 148]. From an energy economics perspective, it is also not yet clearly defined whether the application can be assigned to BTM or FTM, as it has clear grid-serving properties. However, since there are also approaches that directly incentivize consumers to compensate their own reactive power, it also shows characteristics of a BTM application [147, 149].

Black start A black start or black start capability describes the characteristics of a technical unit to restart the power flow of electricity in an energy system without the support of an external power supply. As the name suggests, this is necessary after an outage or a blackout situation. Historically, industrial turbines have been used to enable black start. Although there are ongoing efforts to make grids more stable and to avoid large-scale blackouts, it is becoming apparent that energy storage systems can also be used for this application [150]. Since blackouts are always evaded and occur very rarely, there are no established markets yet where entities offer their black start capability [151]. Also, blackouts are difficult to predict [152], so such storage systems are classically operated with other applications as well [153, 154]. In the event of a blackout, these storage systems would provide their power and energy to enable other technical units to come online and restore the grid to a robust state [150]. Depending on the size and location of the grid, the power and energy required for this must be scaled respectively [155].

Island operation Similar to the black start application, energy storage systems in island operation are also working without the support of an external grid. In contrast to black start, in this application the energy storage system is used not only for the initial grid buildup, but for the entire grid operation [156, 157]. For this purpose, the storage unit is used to smooth peak loads and to balance generation and consumption. This application is used on smaller islands that do not have access to other electricity grids. Characteristically, these energy storage systems are used in island operation with renewable energy sources such as PV generators or wind turbines [158, 159] and replace, for example, the historically necessary startup of diesel generators if the energy supply of the renewable energy sources is not sufficient [160].

Uninterruptible power supply The background and motivation for the uninterruptible power supply application are power failures in the supply network. Compared to a blackout, where a grid failure occurs over a large area for hours or longer, the uninterruptible power supply aims to compensate for smaller grid failures over a short period of time with the help of energy storage [161]. Like the peak shaving application, the SOC is kept at a high level for the most effective operation of the application [162]. If the supplying grid were to fail, the systems to be supplied can continue to be fed with electricity from the energy storage system. Economically, this application can be especially lucrative for industrial consumers, as the sudden power outage for production lines can lead to serious damage to equipment [163]. Like the black start application, this application is difficult to predict, making its techno-economic value dependent on the respective installation site and energy system.

Renewable energy integration The expansion of renewable energies can be observed throughout the entire electricity value chain. From the low-voltage side at households, where PV generators of a few kWp are installed on the roof [44, 78], to PV ground-mounted power plants and wind parks in the GW range. Such large-scale power plants are integrated into the electricity grid due to their capacity at medium and high voltage levels, and their electricity is usually traded directly on spot markets or using power purchase agreements [164, 165]. Since prices on these markets are subject to fluctuations due to volatile supply and demand, and the operators of large PV farms and wind parks want to achieve the highest possible remuneration prices, energy storage facilities are increasingly being installed at renewable energy sites [166]. These energy storage systems intend to temporarily store surplus energy (like the self-consumption increase application) and to store electricity when market prices are low and to discharge the electricity when market conditions are more attractive [167].

Peer-to-peer trading As the name suggests, peer-to-peer trading describes electricity trading between different peers [168, 169], which in turn describe electricity consumers. If all or some of these consumers also have generation facilities, they are also referred to as prosumers (producing consumers) [170, 171]. Since these prosumers, depending on their generation units, can also have excess electricity, many prosumers also invest in energy storage systems (see SCI application in Section 2.2) [82]. The flexibility of these energy storage systems, in the form of stationary and mobile storage, allows excess energy to be temporarily stored in the storage to use it for other applications or in times of higher consumption [44, 45]. In the peer-to-peer trading application, not only can excess electricity be traded between consumers and prosumers, but also the flexibility provided by the energy storage systems. In this context, the boundaries between the consumer/prosumer are softened and extended to the community [45, 169, 172]. This leads to models where EMSs no longer decide on the consumer level, but on the community level about the generation units, energy storage, and consumers, which is further explained in Section 2.4, of *multi-storage* systems.

2.3 Multi-use operation

As introduced in Section 2.2, battery energy storage systems are a multi-purpose technology [24, 173], which can serve both BTM and FTM applications [69, 70]. Since these energy storages can be operated very differently, depending on their selected application, dimensioning, and input variables, such as parameters and profiles, the utilization of the energy storage also varies [82, 85, 102]. Two similar metrics of utilization ratios have been presented in literature [34, 174]. The shown metrics in Equations 2.12 and 2.13 relate to the energy throughput and the utilization of the energy storage system over time. Here, the $E^{\text{throughput,actual}}$ and $E^{\text{throughput,max}}$ relate to the actual and maximum energy throughput at the storage, while $t^{\text{operation,total}}$ and $t^{\text{operation,active}}$ denote the total operation time and the operation time during active charge and discharge of the system. Since the utilization ratios of energy storage systems with only one application (so-called single-use operation) can be less than 10 % [34], and therefore a lot of potential remains unused, the idea of maximizing the utilization and thus the added value of the storage system is obvious [18, 175].

$$\tau^{\text{energy}} = \frac{E^{\text{throughput,actual}}}{E^{\text{throughput,max}}} \tag{2.12}$$

$$\tau^{\text{temporal}} = \frac{t^{\text{operation,active}}}{t^{\text{operation,total}}} \tag{2.13}$$

A promising approach, which is becoming increasingly established not only in research but also in industry, is the stacking of applications, the so-called *multi-use* operation of energy storage systems [29, 123]. This operation is defined by two or more applications served simultaneously or consecutively on a single energy storage system [176, 177]. By reducing the idle times of the system, synergies between applications are exploited to ultimately increase the techno-economic potential. In addition to the selected applications to be stacked, the technical parameters and capacities of the energy storage and the EMS play a central role for the operation [123]. In the further course of this section, the concept of *multi-use* is explained, first using large-scale stationary storage systems, and second, EVs.

2.3.1 Allocation of storage capacities

Allocation of energy To serve multiple applications on one storage unit, the EMS needs to allocate the technical capacities of the system to the applications. An essential parameter of the storage capacity is defined by the energy content [29, 123]. For lithium-ion batteries, this energy is defined by the charge of the battery cells and the voltage potential of the system. The nominal energy content of the system is thus divided among the applications to be allocated, whereby the sum of the allocated energy content per application may not exceed the total nominal energy content [63, 176]. From a regulatory perspective, it is also necessary to prevent energy shifts between FTM and BTM applications. Energy shifts between applications of the same group (FTM or BTM) are permitted and do comply with unbundling laws [29].

Allocation of power In addition to energy, the second technical parameter of energy storage systems is the power that can be provided by the system. This parameter is defined and limited by the maximum C-rate of the battery cells. The second limiting factor is the rated power of the storage system's power electronics. Finally, the maximum charge and discharge power depends on the C-rate, the power electronics, as well as the actual energy content of the battery, and can be allocated to the applications served [63, 176]. For the topic of FTM and BTM, the same regulatory requirements apply to power as to energy, since the power electronics enable the coordinated power provision to either BTM or FTM applications. While previous literature has emphasized the importance of allocating energy, the allocation of power, though equally important, has been omitted [123].

Allocation of time Due to the temporal relationship between the technical capacities, energy and power, it is also decisive for *multi-use* operation how long applications can or should be served. As explained in more detail later for the *multi-use* types, time plays a decisive role for the EMS. Since many applications, such as frequency regulation or spot market trading, have regulatory minimum delivery periods [111, 116], these conditions must be incorporated into the operating strategy. By taking this variable into account, the utilization of the storage system can be optimized, where a high proportion of allocated time for a specific application can also increase its energy throughput.

Allocation of priority Depending on the selected algorithm of the operating strategy, it may be necessary to assign a priority ranking to the applications in the *multi-use* strategy. The prioritization of applications additionally helps to allocate limited capacities of the storage system. If imbalances between allocation and demand of applications occur, they can be solved through prioritization [63]. This means that a higher-priority application is allocated energy and/or power, and afterwards the remaining capacity is allocated to other lower-priority applications [176].

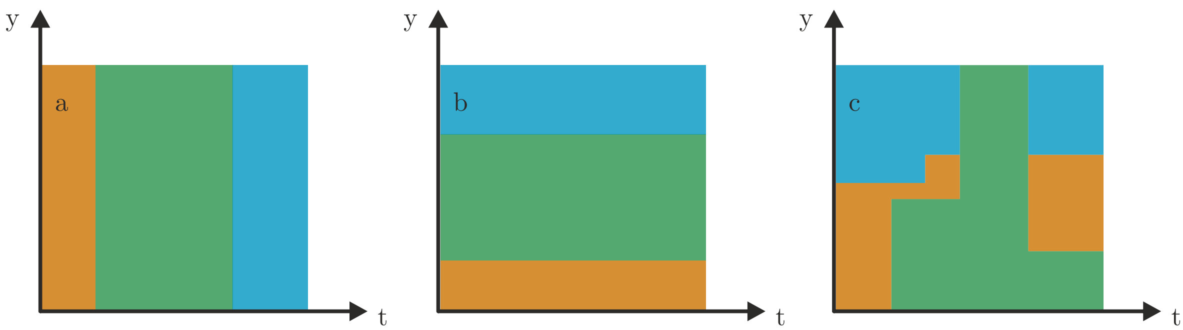

Figure 2.1: Exemplary illustration of the three *multi-use* types: sequential (a), parallel (b), and dynamic (c) *multi-use*. The colors describe the served applications and their allocated storage capacities. The figure is adapted from [46].

2.3.2 Sequential multi-use

When it comes to performing *multi-use* on energy storage devices, a distinction is made between three *multi-use* types. With the first type, sequential or serial *multi-use*, the entire capacity of the storage is allocated exclusively to one application at a time (cf. Figure 2.1a). This has the advantage that for each point in time, the EMS focuses on one application only [29, 63]. The degree of freedom in this *multi-use* type is time. Depending on the possible switches between applications, the storage operation can be further optimized. If the period for switching times between applications is reduced, the frequency for new decisions and therefore the complexity for the EMS is increased. Due to the higher frequency of switching possibilities, the energy management can intervene more often and decide which application brings the highest added value and should be served exclusively in this moment.

2.3.3 Parallel multi-use

Unlike sequential *multi-use*, the allocation of energy and power in parallel *multi-use* remains constant over time. This form of *multi-use* can serve several applications simultaneously. For this to happen, the EMS must be aware of or able to calculate the allocated shares of energy and power. As shown in Figure 2.1b, these allocation values remain constant over time [63]. This operation is particularly well suited for the operation of applications that require the energy storage to be as constant as possible, such as frequency containment reserve and spot market trading.

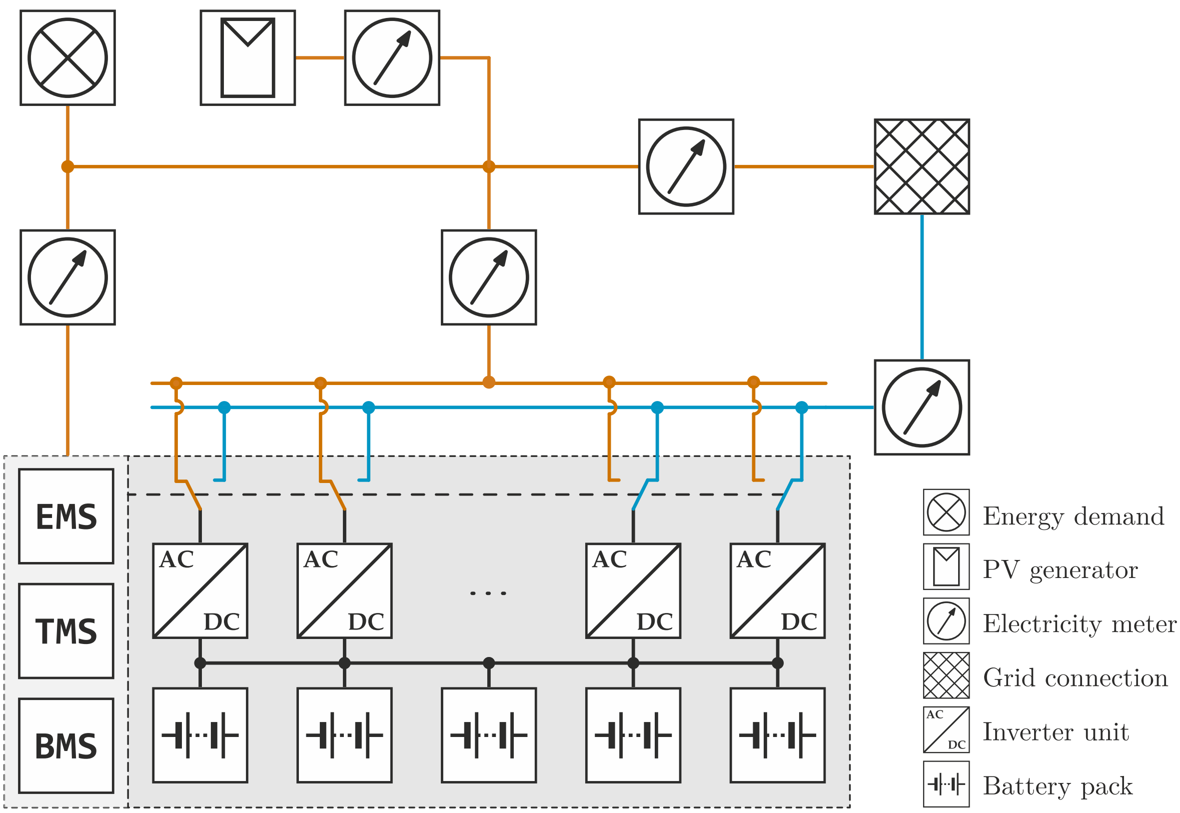

Figure 2.2: *Multi-use* topology for a large-scale battery storage system with multiple inverters, electricity meters and periphery unit (energy management system (EMS), battery management system (BMS), and thermal management system (TMS)). With the chosen topology, the storage system can serve behind-the-meter (BTM, orange lines) and in front-of-the-meter (FTM, blue lines) applications. The figure is adapted from [46].

2.3.4 Dynamic multi-use

Dynamic *multi-use* is a hybrid strategy of sequential and parallel *multi-use*. By acquiring the advantages of the two predecessors, an EMS with dynamic *multi-use* can distribute the technical capacities of the energy storage system over multiple applications simultaneously. In addition, it can change the allocation of capacities over time to always foster applications with the highest added value (cf. Figure 2.1c). Depending on the number of possible applications and the frequency of the switching time, it is the most complex type of *multi-use*, but also with the highest potential, as discussed further in Chapter 5.

2.3.5 Multi-use topology for large-scale storage systems

To implement the *multi-use* types presented in a real system, the regulatory conditions for the corresponding applications must be met in addition to the technical requirements of the energy storage system. In the *StorageLink* research project (funded by the Bavarian Ministry of Economic Affairs, Regional Development and Energy, grant number IUK-1711-0035), a topology was designed that allows both BTM and FTM applications to be served simultaneously [178]. In Figure 2.2 this topology is shown with an energy storage and the possible power flows (BTM in orange and FTM in blue). In the topology the battery cells are integrated in modules. These modules are in turn connected via a DC busbar, which allows the connected inverters to access the capacity of the modules continuously. The design of the power electronics with multiple inverters and the possibility of switching between BTM and FTM, allows the operation of BTM and FTM applications. To comply with legal requirements, the power flows between the technical components are documented with calibrated electricity meters [63]. For this purpose, one electricity meter each is installed on the BTM and FTM busbars, which document how much and when energy is charged to or discharged from the battery storage. Since the necessary peripherals (energy management, battery management, thermal management) for the storage have a consuming character, they are also assigned to the BTM side and provided with a separate electricity meter. Depending on the generation plants within the corresponding energy system, this must also be equipped with an electricity meter [178]. With the calibrated meters shown in Figure 2.2, the EMS can control the energy storage with BTM and FTM applications in compliance with the legal requirements [29]. Based on the research project *StorageLink* and the topology [178], the existing simulation tool *SimSES* was extended and the optimization framework *mu_opt* created, which is further explained in Chapter 5 [63, 176, 179–182].

2.3.6 Electric vehicle multi-use

As EVs are parked most of the time, using the vehicle's traction battery for other applications is an obvious next step [183, 184]. Ideally, *multi-use* operation would also be applicable with mobile storage systems, as for large-scale storage systems, to increase the added value of the battery. Compared to stationary storage, EVs differ in several aspects [185]. First, by their very nature, EVs are not connected to the electricity grid when they are on the road or unplugged. This makes it even more important to know the connection times to the electricity grid for mobile energy storage systems [186]. Second, mobile storage systems do not have a fixed point of common coupling. Typically, vehicles are used for transportation between home, office, shopping, etc. [187]. With the integration of electric charging stations, EVs can and will be connected to the grid at different locations. Third, EVs or their chargers do not have built-in power electronics with multiple switchable units that allow the physical measurement of BTM and FTM power flows. To enable a physically and regulatory viable solution for *multi-use* operation with EVs, an alternative to calibrated electricity meters in stationary energy storage must be found. One possibility to document the incoming and outgoing power flows of the BTM and FTM partitions would be a calibrated EMS. This EMS must be able to document the corresponding power flows and energy contents of the partitions transparently, consistently, and securely at any time and store them within the vehicle. In this way, it will be possible to implement established *multi-use* strategies with EVs, or fleets of them, and to exploit the advantages of these approaches. With an optimization framework, a detailed analysis on *multi-use* with EVs is conducted, which is presented in Chapter 6 [47, 188].

The multi-use research aims are summarized into the following three research questions:

- *What are the techno-economic results of a multi-use operation strategy on a stationary storage that allocates both energy and power capacities?*
- *What energy system topology is required for such an implementation and how does the virtual partitioning into BTM and FTM influence the success of a multi-use strategy?*
- *What is a possible methodology design that enables the implementation of a multi-use operation strategy on a fleet of EVs that serve the primary application of mobility provision?*

The existing literature gaps motivating the question formulation and the resulting findings can be found in greater detail in Chapters 5 and 6.

2.4 Multi-storage operation

Decentralized generation of electricity is an increasingly important aspect of the modern energy mix [24]. Virtual power plants in particular play a decisive role [189]. These virtual power plants describe the combination of several generation plants, electricity consumers, and flexibilities [190]. The generation units are typically decentralized PV generators or wind turbines. Electricity consumers are households as well as commercial and industrial consumers. By being able to both charge and discharge energy, energy storage systems provide a source of flexibility to ensure the balance between generation and consumption in the virtual power plant [191]. The provided flexibility enables the system of generators and consumers to stabilize the electricity grid as well as to offer other services within and outside the energy system [168, 169]. To achieve the objectives and maximize the added value of the technical assets, it is now necessary to control the flexibilities as well as possible. This task is particularly challenging when several decentralized storages are to be controlled and operated together [169, 192] – the so-called *multi-storage* operation.

2.4.1 Multi-storage on entity level

As described in Section 2.2, an energy storage can serve a variety of applications for an electricity consumer. Both residential and commercial entities are investing in stationary and mobile battery storage systems. Once the investment for such energy storage systems has been made and more than one of these energy storage systems has been installed, the question arises as to how they should be operated in a way that maximizes their value [44, 193]. A well-researched combination of such energy storage systems is, for example, a home storage system and an EV in the same household. Unless these systems have already been acquired as an integrated system, each energy storage system has its own mode of operation. For example, the home storage system will try to store as much excess energy as possible to increase self-consumption [78, 82], and the vehicle will request energy from the charger if the SOC of the storage system falls below a certain threshold [187]. To use the synergies of the energy storage systems as efficiently as possible, the EMSs must be bundled and communication enabled. To stay with the example of the household, the EMS should be able to read all power flows in the energy system and react accordingly [194]. Instead of the home storage only maximizing self-consumption in the building, added value can be created if the vehicle battery is also charged with self-generated electricity. It should be noted that within energy systems with multiple energy storage systems, the possibility for optimization does exist, if the EMSs can access and intervene with each other. Using the example of a German household, this issue has been further investigated in Chapter 3.

2.4.2 Multi-storage on community level

As described in the previous paragraph, it adds value to operate energy storage systems within an entity not autonomously, but as a combined unit, to utilize their advantages and synergies. If one now links several entities, which in turn are equipped with flexibilities, the situation becomes no less complex, since each entity now represents a separate stakeholder in the formed community. The formation of such a community is observed, for example, in peer-to-peer markets, which have been described in Section 2.2. For the efficient provision of the flexibility potential of energy storage systems, the exchange of information between the storage systems is once again at the forefront [169, 192]. Compared to the individual entity or stakeholder, data protection regulations can complicate the exchange of information in the community. To assess the potential of *multi-storage* operations, an empirical study is conducted to investigate *multi-storage* operation in a peer-to-peer market (cf. Chapter 4). In addition to evaluating bidirectional EV charging and battery degradation, the study focuses on the EMSs and their decision-making approach. For this purpose, centralized and decentralized decision-making is analyzed for the operating strategies of the batteries (cf. Figure 2.3).

Decentralized decision-making describes the characteristic that the entities in the system each have their own EMS, which determines the optimal operation based on the locally available data. Within a community, this means that each entity only has access to its own data and has no knowledge of the technical and economic status of the other entities. From a data protection point of view, this procedure raises few concerns, and the degree of computational complexity for the EMS is also limited, since relatively little data needs to be considered for the calculation of the optimal operation strategy [45, 169].

Compared to the decentralized approach, where the added value for the individual is maximized, the centralized approach can maximize the added value for the individual and the community [77]. To do this, a central EMS must be able to retrieve all necessary data within the community and control all flexibilities in the energy system. For this to work, sharing data across the boundaries of the entities and stakeholders must be possible. While it is not necessary for entities to have visibility into the data of other entities, the central EMS must have full visibility and execution power. The higher degree of flexibility also increases the computational complexity for the EMS, which is why it is important to consider the trade-off between the degree of flexibility and the degree of complexity [45].

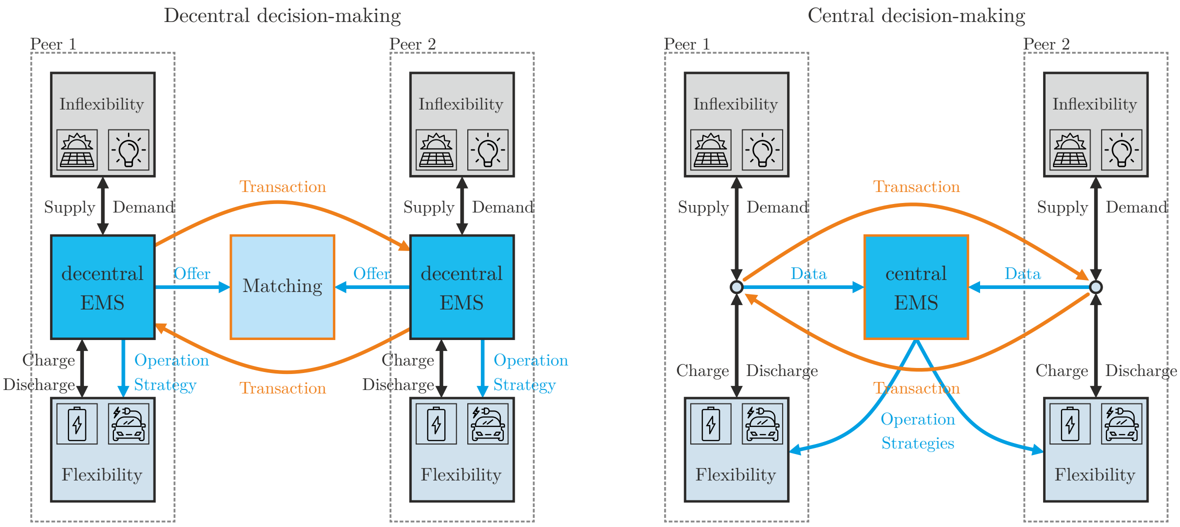

Figure 2.3: Decentralized (left) and central (right) decision-making approach in a peer-to-peer network. Each peer is characterized by its energy inflexibilities (producing and consuming components) and flexibilities (stationary and mobile energy storage). For the decentralized approach a decentral energy management system (EMS) at each peer calculates the offers and transfers them to the matching platform of the peer-to-peer network. With the larger information base and flexibility pool, the central EMS simultaneously calculates the optimal operation strategies for all flexibilities and peers. The figure is adapted from [45].

2.4.3 Aggregator operation

Due to application-specific requirements, it is necessary for some markets to fulfill certain technical conditions with the energy storage device [108]. Examples of these requirements are minimum power or minimum provision periods that must be met to participate in respective markets [108, 116]. Since energy storage systems that cannot meet these requirements are excluded from these markets, a solution to this problem is to operate multiple energy storage systems together in *multi-storage* operation and to market them as a cumulative storage system. Entities that enable this bundling of several energy storage systems are defined as aggregators [195, 196]. Aggregators are used both in the area of stationary energy storage and with EVs. Since the ownership of the energy storage systems also plays a decisive role in this context, two aggregator models will be presented, using the example of EVs.

Assuming there is a commercial electricity consumer owning a fleet of EVs, who wants to participate in the FCR market. Since a minimum capacity of 1 MW applies [108], none of the EVs can participate in the market as a single player. Nevertheless, to meet the minimum requirements, the EV fleet can be aggregated as a cumulative flexibility [195, 197], and thus meet the market requirements. A detailed study of this aggregator model applied to a commercial electricity consumer is presented in Chapter 6.

The second aggregator model differs in the aspect that the vehicles are now owned by multiple owners rather than a single entity. Due to the technical requirements, still none of the owners would be able to participate in the desired market. Here, too, an aggregator could remedy the situation by consolidating the capacities of the battery storage units. In contrast to the first aggregator model, the operator and thus marketer of the consolidated energy storage system is not the owner of the technical units. As already established for stationary energy storage, an agreement would have to be reached between the aggregator and the vehicle owners on how the risks and revenues of the applications served are to be shared.

The multi-storage research aims are summarized into the following three research questions:

- *What are the techno-economic effects of both stationary and mobile (EV) energy storage within one residential system?*
- *When combining energy management systems and peer-to-peer trading in a local electricity market, how do the techno-economic results compare between a decentral versus central decision-making approach?*
- *What impact does the size of the EV fleet have on the techno-economic performance per vehicle?*

The existing literature gaps motivating the question formulation and the resulting findings can be found in greater detail in Chapters 3, 4 and 6.

2.5 Optimized energy storage management

In general, the EMS of an energy storage system has the task of executing the defined application or operating strategy as optimally as possible, increasing the added value of the storage system by using prediction data, while complying with technical and regulatory requirements. An EMS needs to be real-time capable, however real-time optimization is computationally demanding. Figure 2.4 illustrates a robust concept for an EMS that combines prediction, optimization, and real-time capable implementation of an optimized energy management for an energy storage system [46].

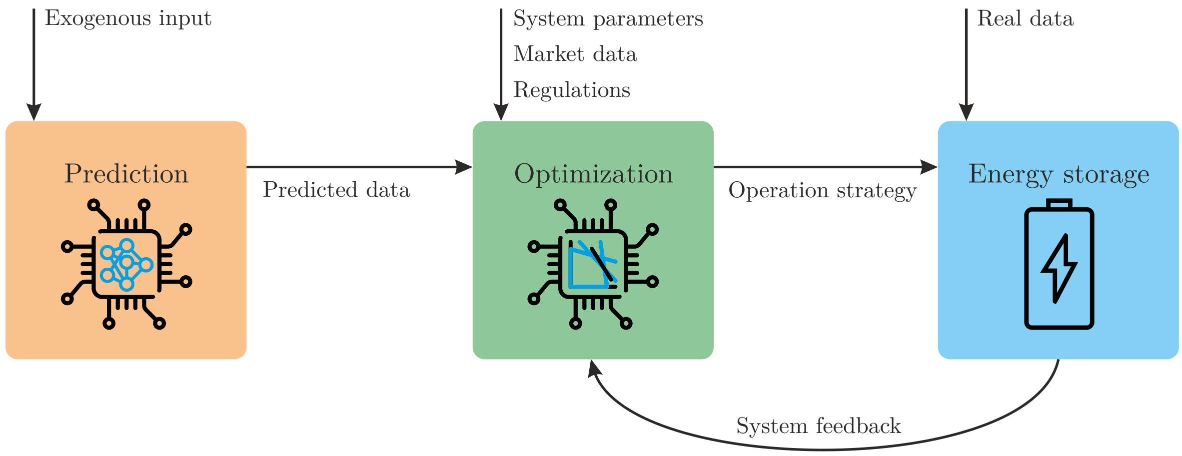

Figure 2.4: Proposed method for the practical implementation of battery energy storage systems' optimized operation strategies. Necessary data, such as power demand and supply are predicted. The output data from the prediction, as well as system parameters, technical states, and regulatory constraints are received by the optimization model. Optimizations are executed with each addition of new information and the calculated operation strategy is sent to the energy storage. To ensure a close coupling of the energy storage and the optimizer, there is a feedback loop with the current system states of the energy storage. The figure is adapted from [46].

2.5.1 Prediction of data

Since an optimal operating strategy should not only reflect and consider the current conditions and status of the energy system, but also future developments in and surrounding the system, a temporal prediction is necessary. This prediction of data should reflect the future development of input profiles, parameters, and system states as accurately as possible [41, 42, 198]. Depending on the applications, the profiles to be predicted include data for spot market prices, expected frequency curves, and predictions of power flows in the energy system [199, 200]. Depending on the systematic or non-systematic correlations and availability of data, some profiles can be predicted more easily than others.

A central component for the prediction of data is that a relationship between the input variable and the output variable to be predicted is assumed or learned. To make this possible, there are different possibilities and algorithms that can be used. One method for predicting time series is linear regression [201]. This is a comparatively simple method that assumes direct linear relationships between the exogenous variables and the output predicted variable [202]. With the help of several influencing variables and real data, the linear regression can be trained and by weighting input variables, the time series prediction is calculated. Another well-known representative for prediction algorithms is the support vector machine [203]. Designed for classification and regression of data, the support vector machine allows to establish relationships between data sets and can train them [204]. Originally developed to classify linear relationships, the decision function can also be adapted to classify non-linear relationships [205]. The adaptation of the decision function is done by choosing a suitable kernel function and adapting the features.

Artificial neural networks are another well-known representative of prediction algorithms, which is becoming increasingly popular. Based on research in the field of neuroscience, attempts are being made to approximate artificial neural networks to the human brain with the aid of hidden layers and neurons [206, 207]. Also in this approach, there is an input and output layer, which in turn can be occupied by neurons. By using historical input and output data, a defined neural network is trained. The training serves to induce the neurons to establish correlations between input and output data and to reproduce their relationship as well as possible [207]. Each neuron of a layer can be connected to any other neuron of the neighboring layers. The internal weights of the individual connections between the neurons and layers can be used to strengthen the performance of the neural network. Depending on the chosen architecture or structure of the neural network, a better result for the prediction can be achieved. Literature has shown that increasing the number of hidden layers or neurons does not automatically improve the prediction result [199]. Rather, an artificial neural network should be parameterized depending on the input data and the desired prediction period [208, 209]. Over-fitting of neural networks describes that data during training can map the correlations of the training input and output data but has large prediction errors when predicting with new data [199].

The quality of prediction data or its prediction error can be determined with different metrics. Since there is no consensus in the literature as to which metric is the best, but rather this depends on the observed scenario, frequently used representatives are: mean absolute error, mean absolute percent error, mean squared error, root mean squared error, mean bias error, and Theil's coefficient of inequality [210, 211]. Since the optimization of the EMS has a strong dependence on the quality of the prediction, one tries to minimize the prediction errors. There are different possibilities, like the limitation of the prediction horizon [212]. It is in the nature of prediction values that its complexity increases and accuracy decreases with a rising forecast horizon. Another approach of improving the handling of the prediction uncertainties in the EMS is to strengthen the data exchange between the prediction algorithm and the optimization, which is shown in Section 2.5.4.

2.5.2 Optimization of operation strategy

Optimization algorithms have in common that they want to fulfill a desired objective function. The objective function can be fulfilled by changing the system states, the so-called decision variables, which offer degrees of freedom to the system [213]. Depending on the structure and complexity of the problem to be solved, there are different algorithms and methods. In literature, three groups of algorithms are distinguished: exact solution approaches, heuristics, and meta-heuristics [214, 215]. Within each group, there are different solution techniques. For example, algorithms such as the linear problem, non-linear problem, or quadratic problem belong to the exact solution techniques [216]. As the name suggests, non-linear or quadratic approaches can map non-linear or quadratic constraints in the objective function or the constraints to be met. Due to their more complex algorithmic structure, these exact solution approaches are usually slower than linear problems [194], which will be described later. Within the group of heuristics one can find representatives, such as the fuzzy method, greedy heuristic, and gradient method [217, 218]. Because of the structure of heuristics, they can reach the objective function relatively fast, but have the disadvantage that they can terminate in local optima [194], which is why there is often no guarantee for finding the global optimum. This problem can be improved by meta-heuristics. Evolutionary approaches, swarm intelligence, and neural networks belong to this group [219]. Based on processes from natural science, these algorithms allow a step-wise worsening of the objective to prevent the algorithm from getting stuck in local optima [194]. Although meta-heuristics are comparatively fast, they have a lower robustness and reliability in locating the global optimum compared to mathematical optimization approaches such as linear optimization [220, 221].

Linear programming As described above, linear programming approaches try to represent processes with linear relationships. Due to their simplified structure, compared to non-linear approaches, the algorithm is usually able to find the solution for a problem relatively fast and is also able to reach the global optimum after an appropriate computation time [194, 213]. For this reason, this approach, and modifications of it, will be discussed further in this thesis.

To make linear problems solvable with modern processors, the problem must be represented mathematically [222]. For this purpose, the model consists of three essential building blocks: objective function, constraints, and decision variables [213]. In literature, a linear model is generally represented as a minimization problem. The objective of the minimization function could be to minimize the cost of a process. To represent this mathematically in the objective function, the decision variables must be brought into a mathematical context. The objective function shown in Equation 2.14 thus contains the weighting of the decision variables $\mathbf{c}$ and the vector of the decision variables $\mathbf{x}$.

$$\min \qquad \mathbf{c} \cdot \mathbf{x} \tag{2.14}$$

Since optimization problems are supposed to find the best solution for a defined area, the solution space must also be limited. This delimitation is done with the help of constraints and boundaries. As shown in Equation 2.15, the vector of the decision variable can be broken down. Each line in the formula stands for its own constraint. Each of the constraints in turn consists of weights a for the corresponding decision variable x. Generally, the linear problems are constrained by specified bounds, which are implemented in the model as the vector of constants b. This results in the structure of the model with n decision variables and k constraints.

$$\begin{aligned}
a_{11} \cdot x_1 + a_{12} \cdot x_2 \cdots + a_{1n} \cdot x_n &\leq b_1 \\
a_{21} \cdot x_1 + a_{22} \cdot x_2 \cdots + a_{2n} \cdot x_n &\leq b_2 \\
&\vdots \\
a_{k1} \cdot x_1 + a_{k2} \cdot x_2 \cdots + a_{kn} \cdot x_n &\leq b_k
\end{aligned} \tag{2.15}$$

In the further course, the solution approach attempts to fulfill the objective function, and in the shown example, to minimize it. The achievement of the objective function must happen in compliance with the constraints. To simplify the constraints, the model can be put into the canonical form shown in Equation 2.16. The mathematical relations between the constraints and the objective function are described here. Therefore, the mathematical relationships of the constraints and decision variables are represented as matrix A and the constants are summarized as b [213]. In addition to the usual constraints, many algorithms also require bounds on the decision variables. The implementation of lower and upper bounds should serve to limit the solution space to the mathematically relevant area and aid to increase the speed of the optimization. In the field of energy storage, such limitations can include the limitation of minimum and maximum charging and discharging power [30]. Given the fact that many relationships in optimization problems require the non-negativity of decision variables $\mathbf{x}$ [223], this is represented in Equation 2.17.

$$A\mathbf{x} \leq b \tag{2.16}$$

$$\mathbf{x} \geq 0 \tag{2.17}$$

Mixed-integer linear programming Although linear problems can be used to represent linear relationships, these approaches have difficulties if there are case distinctions or discontinuous functions in the model [194, 224]. In the field of energy storage, for example, it may be necessary to distinguish whether a storage system is being discharged or charged. Depending on the direction of the current flow, different processes appear. Linear programming is not able to make a case distinction here, which is why the extension of mixed-integer linear programming can be required. As the name suggests, the approach includes all the capabilities of linear programming, with the addition that decision variables can represent both continuous and integer values [224]. Another example is shown in the publications of Chapters 5 and 6, where the buying and selling of electricity on spot markets is represented as an exclusive action. This exclusivity is achieved by means of integer decision variables. Since the desired exclusivity of the power flows (buying or selling) cannot be achieved with continuous variables, but there must be a binding relationship between continuous and integer variables, the *big M* method is used [225, 226]. By implementing further constraints, this method makes it possible to convert continuous variables into integer variables and thus to enable case distinctions in linear problems [225].

2.5.3 Real-time operation

Unlike optimization, real-time operation can deploy a desired operating strategy in real time [179]. To enable this real-time capability, the computational processor must execute the algorithm in the appropriate time and send output signals to the storage system. To make this possible, simple rule-based methods are used, which can make decisions with the help of if-else blocks [94, 227]. Since the complexity is limited by the computing time, real-time operation is inferior to optimization from a techno-economic point of view. However, the advantage of real-time operation lies in the fact that it can work with the actual data, whereas optimization algorithms generally work with predicted values, which in turn are subject to prediction errors. To increase the techno-economic performance of the storage system, a combination of prediction, optimization, and real-time operation is used [45–47], as it is shown in Figure 2.4.

2.5.4 Model predictive control

In this work, only deterministic optimization is used, meaning that perfect foresight is assumed for all input data, albeit with a reduced time horizon. Nevertheless, the model predictive control (MPC) methodology was tested using predicted values within the *StorageLink* research project.

The method describes a form of algorithm that can handle prediction data and process it in an optimization algorithm [228]. With the help of optimization states, the algorithm is able to perform optimization and internally store the results. Since prediction data can change over time, the MPC algorithm must also be able to re-evaluate and, if necessary, adapt the results generated in the past and the optimization states previously created [229]. Here, the rolling horizon optimization comes into play. This algorithm describes the process by which a time series optimization defines the decision variables over a defined period of time, the optimization period. In the field of energy storage systems, the optimization period should be selected in such a way that a corresponding application can be reasonably operated and optimized [46]. The time period depends on the selected application. For the application self-consumption increase with a PV generator, e.g. 24 h is a reasonable period, as it always covers a full day-night cycle. The upper limit for the optimization period is defined by the computational complexity, since for a longer time period an increasing number of decisions must be optimized [213]. The second time aspect, relevant for rolling horizon optimization, is the rolling horizon. This parameter defines how often the optimization algorithm is called. A shorter time period leads to a higher frequency of new optimizations and thus to a higher computational demand. Although the quality of the optimization results can be increased by a higher frequency of iterations, it should always be considered whether the quality increase can also be achieved with the corresponding computational resources. The rolling horizon is closely coupled to the prediction quality. The better the quality of the predicted data, the smaller the prediction error [210]. Since the prediction error for optimization algorithms is mostly unknown, it is difficult to quantify the influence of the prediction uncertainty in the optimization. However, the rolling horizon optimization can perform new optimization runs for each rolling horizon and provide the optimization algorithm with new prediction values accordingly.

To put the MPC framework into the context of energy storage, prediction algorithms are used to predict the necessary parameters and profiles for the optimization period. This prediction data is passed on to the optimization. The optimizer evaluates the prediction data together with other input variables and calculates the optimal operating strategy, subject to regulatory and technical constraints. This operating strategy is sent in the form of control signals to the real-time operation of the energy storage system, where it is processed by the technical unit. To prevent prediction errors, it is highly relevant to send system states, such as the state of charge or the state of health, from the real-world energy storage system to the optimization algorithm. This feedback loop improves the quality of the prediction significantly as it avoids the occurrence of technically unfavorable operating strategies or system states. Due to computational complexity, server solutions are often used in real-world projects [230, 231]. For this purpose, prediction and optimization are performed online and the corresponding control signals are sent to the storage system and its local real-time operation unit [232].

2.5.5 Degradation aware energy management

Like any technical unit, energy storage systems are also subject to a limited lifetime. Since the lifetime of the energy storage unit plays a decisive role in the investment decision as well as for the use of the system, the lifetime or degradation must be considered in energy management [48, 233]. In the further course of this section, the most important aging mechanisms of lithium-ion batteries are discussed and degradation aware optimization approaches are introduced.

For lithium-ion cells the aging behavior can be divided into two groups of processes: calendar and cycle degradation [234, 235]. While cycle degradation processes only occur during active energy throughput by the cell, calendar degradation occurs both during active and idle times [236, 237]. Since semi-empirical degradation models are used in the context of the aging calculation in the further work, the most important processes are also explained based on applied degradation models for lithium-nickel-cobalt-manganese-oxide (NMC) and lithium-iron-phosphate (LFP) based cathode battery cells [238–240]. It is important to note that the degradation processes in the battery are highly complex and can be influenced by a multitude of factors. Thus, depending on the considered battery cell chemistry, the degradation processes and ideal modeling approach can strongly vary.

Energy throughput Derived from the charge throughput, the energy throughput describes energy that is charged and discharged from the battery cell. For battery degradation, literature has shown that there are internal processes ranging from linear [241] to square root [242] relationships between energy throughput and aging. It was shown that the capacity fade is determined by a square root relation to the energy throughput and that the internal resistance increase follows a linear pattern [238].

State of charge The degradation models used in this work [238–240], show a relationship between the voltage level – and therefore the SOC – and the battery cell degradation. From a calendar degradation perspective, literature has proposed a linear correlation between degradation and voltage level [234]. For the cycle aging, it should be mentioned that the energy throughput around a medium SOC leads to relatively low capacity fade and resistance increase [238, 240], which emphasizes that voltage levels in the lower or upper voltage range should be actively avoided by the EMS.

Cycle depth This metric defines the SOC change of a cycle or a part of it. There are different ways to define a cycle or half cycle – an established approach is the rain-flow algorithm [243, 244]. Published measurements in literature have shown that the depth of discharge has an exponential effect on the capacity fade [240, 245]. Whereas small C-rates, and thus small SOC changes, lead to reduced degradation losses, a large depth of discharge shows exponentially higher capacity losses [240]. Due to this non-linear relationship, simplified models applying the Wöhler curve for the dependence of cyclic aging have been proposed in literature [55, 246].

Time As described, lithium-ion cells have a limited lifespan, which is also linked to time. Literature highlights that the formation of the solid electrolyte interface is the dominant effect of calendar degradation [247]. This layer is created over time by decomposition products of the electrolyte and consumed lithium. Due to the decreasing nature of these internal processes over time, the time dependence of the aging can be described as a square root function [248, 249].

Temperature Based on the two semi-empirical degradation models, the influence of temperature on storage degradation is implemented differently. In the work of Schmalstieg et al. the temperature only influences the calendar degradation [238]. In comparison, Naumann et al. attribute temperature to calendar and cycle degradation [239, 240]. Both models list the Arrhenius equation as the primary reason for the aging influence of temperature [250]. This equation states that chemical processes, for which an activation energy must be applied, occur more rapidly at higher temperatures [251]. In the context of lithium-ion batteries, this means that degradation proceeds faster at higher temperatures.

Although no new degradation models are developed in this work, the importance of battery cell degradation on the operating strategy of energy storage systems is demonstrated. The active consideration and therefore avoidance of battery degradation can be applied on the optimization level of an EMS. To enable this, the optimizer is fed with the necessary prediction values. In Chapters 4 to 6 such degradation aware optimization approaches are shown [44–47]. Since the internal degradation processes also show non-linearities, which lead to longer computation times, simplified degradation aware approaches are implemented. These take into account the dependence on energy throughput [45–47]. Together with the presented MPC framework, it is shown in the following chapters how optimization algorithms and semi-empirical degradation models from literature can be used in parallel. For this purpose, a quasi-stationary degradation state is assumed within the optimizer for time periods of one day or less and an optimized operating strategy is calculated. Based on this operating strategy, the respective degradation model is executed at regular intervals and the calculated SOH is sent back to the optimizer for the next iteration. During the doctoral studies, integrated degradation models were also modeled and analyzed in optimization algorithms. For this purpose, non-linear relationships of SOC, C-rate, etc. were linearized and integrated into optimization models, but due to the computational complexity, the MPC framework proved to be the more promising solution.

The optimization related research aims are summarized into the following two research questions:

- *How to enable a practical implementation of a sophisticated EMS that uses limited perfect foresight and is able to handle prediction values?*
- *What is the techno-economic benefit of incorporating degradation awareness in the storage's energy management?*

The existing literature gaps motivating the question formulation and the resulting findings can be found in greater detail in Chapters 3 to 6.

3 Bidirectional charging in a multi-storage context

In this chapter, the research article titled *A techno-economic analysis of vehicle-to-building: Battery degradation and efficiency analysis in the context of coordinated electric vehicle charging* is presented. This paper examines the influence of different charging strategies for EVs. From a techno-economic point of view, the vehicle-to-building (V2B) technology is analyzed. The setting is a private household that, in addition to the electricity consumption for the building, also has a PV generator and a home energy storage system. Throughout the study, values for an average German household are used for dimensioning. Focusing on a residential context, this paper evaluates the extent to which the EMS within the household can be optimized to yield the highest added value. To do that, the study examines three EV charging strategies:

- Simple charging: The EV battery's SOC is maximized, and therefore the EV is charged as soon as the vehicle is connected to the building via its wallbox.
- Optimized charging: As the simple charging, the wallbox only supports unidirectional charging, however, the EMS optimizes the power flow to the EV. Therefore, the EMS defines when and how much power is provided to the EV.
- V2B connection: In addition to the unidirectional charging, the power flows during the V2B operation are also optimized and bidirectional charging is allowed.

To simulate the effects on the mobile and stationary battery storage systems the linear optimization framework *lp_opt*[1] is developed. This algorithm allows the calculation of optimized power flows within the household, while minimizing the electricity costs. For the EV battery a lithium-nickel-cobalt-manganese-oxide (NMC) based cathode cell chemistry and for the home energy storage a lithium-iron-phosphate (LFP) based cathode chemistry is defined. To validate the findings from the optimization algorithm, the simulation tool *SimSES*[2] is used [179]. Within the simulation tool, the existing battery cell, efficiency, and degradation models are utilized. To investigate the significance for different user behavior of EVs, a distinction is made between commuter and supplementary users [252], as well as a comparison to a passenger vehicle with an internal combustion engine. The objective function of the model aims to minimize the cost of electricity and maximize the profit for the household. Since households in Germany only have an energy-related tariff structure [84], the remuneration from sold electricity is maximized and the costs for purchased electricity are minimized. Due to the significantly higher purchase price for electricity [68], the EMS will primarily try to use energy from its own PV generator directly. If, despite direct self-consumption, there is still a surplus of PV power, this surplus energy will be stored in the stationary and mobile battery energy storage systems. This stored energy can be used later to drive the EV or to cover the consumption in the building.

The analysis of the simulations shows that in households without home energy storage, a strong reduction in OPEX, and thus in electricity costs, is observed when an optimized charging scheme is

[1] Code is publicly available at the Gitlab repository: `https://gitlab.lrz.de/open-ees-ses/lp_opt`
[2] Code is publicly available at the Gitlab repository: `https://gitlab.lrz.de/open-ees-ses/simses`

used. The implementation of bidirectional charging yields further cost savings, but these are less pronounced. In the simulations with stationary storage, the cost reduction as well as the self-consumption and self-sufficiency rate could be further increased. Comparing the results with those of a household without a stationary storage, the improvements with home storage are relatively smaller, leading to the conclusion that an EV and home storage in a household is not necessarily lucrative, as the cost savings must compensate the required investment costs.

Overall, this study presents an EMS that is capable of coordinating the operation of a stationary home energy storage and the charging of an EV in a residential setting. The coupling of the linear optimizer and the simulation tool allows both solving the defined optimization function and the simulation of the non-linear processes in the energy storage systems. By emphasizing on the techno-economic outcome and the storage degradation, the trade-off between economic minimization of electricity costs and storage degradation is demonstrated. Finally, the paper shows that increasing flexibility – in the form of energy storage – increases self-consumption and self-sufficiency rates but saturates with further increases in flexibility. This effect is particularly strong in the scenario with bidirectional EV charging and home storage. Not only are the marginal increases in self-consumption and self-sufficiency rates reduced, but the storage units are cannibalizing each other, making the home energy storage economically obsolete.

Author contribution Stefan Englberger developed the idea of the study, developed the linear programming framework, carried out the simulations, and analyzed the data. Holger Hesse helped to develop the model and to analyze the data. Daniel Kucevic helped to integrate the SimSES simulation tool. The manuscript was written by Stefan Englberger and was edited by Holger Hesse, Daniel Kucevic, and Andreas Jossen. All authors discussed the data and commented on the results.

A techno-economic analysis of vehicle-to-building: Battery degradation and efficiency analysis in the context of coordinated electric vehicle charging

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Article

A Techno-Economic Analysis of Vehicle-to-Building: Battery Degradation and Efficiency Analysis in the Context of Coordinated Electric Vehicle Charging

Stefan Englberger *, Holger Hesse, Daniel Kucevic and Andreas Jossen

Institute for Electrical Energy Storage Technology, Technical University of Munich (TUM), Arcisstr. 21, 80333 Munich, Germany; holger.hesse@tum.de (H.H.); daniel.kucevic@tum.de (D.K.); andreas.jossen@tum.de (A.J.)

* Correspondence: stefan.englberger@tum.de; Tel.: +49-89-289-26969

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Abstract: In the context of the increased acceptance and usage of electric vehicles (EVs), vehicle-to-building (V2B) has proven to be a new and promising use case. Although this topic is already being discussed in literature, there is still a lack of experience on how such a system, of allowing bidirectional power flows between an EV and building, will work in a residential environment. The challenge is to optimize the interplay of electrical load, photovoltaic (PV) generation, EV, and optionally a home energy storage system (HES). In total, fourteen different scenarios are explored for a German household. A two-step approach is used, which combines a computationally efficient linear optimizer with a detailed modelling of the non-linear effects on the battery. The change in battery degradation, storage system efficiency, and operating expenses (OPEX) as a result of different, unidirectional and bidirectional, EV charging schemes is examined for both an EV battery and a HES. The simulations show that optimizing unidirectional charging can improve the OPEX by 15%. The addition of V2B leads to a further 11% cost reduction, however, this corresponds with a 12% decrease in EV battery lifetime. Techno-economic analysis reveals that the V2B charging solution with no HES leads to strong self-consumption improvements (EUR 1381 savings over ten years), whereas, this charging scheme would not be justified for a residential prosumer with a HES (only EUR 160 savings).

Keywords: battery degradation; battery energy storage system; charging scheme; efficiency; electric vehicle; linear programming; lithium ion battery; operating expenses; residential battery storage; vehicle-to-building

1. Introduction

Increasing environmental awareness, technical improvements, and favorable regulatory conditions have all allowed the market for electric vehicles (EVs) in Germany and worldwide to experience an upturn [1,2]. Simultaneously, an increasing number of electricity consumers are investing in renewable energy sources. Photovoltaic (PV) power generators especially benefit from a growing popularity in residential homes, allowing these customers to reduce electricity costs and rendering them as prosumers [3]. A home energy storage system (HES) can be added to further increase self-consumption and self-sufficiency rates [4].

In literature, HESs and EVs are well-researched topics [4–6], however, combined approaches of both storage systems are still a very young research field [7]. While recent literature presents a novel energy management system (EMS) for residential buildings with HES and EV, the contribution comes short on analyzing the technical characteristics of the battery energy storage systems (BESSs) at varying charging schemes [7]. In this work, we analyze how the aforementioned trends may interact, conduct a full techno-economic system analysis and reveal how prosumers with an EV may be able to optimize their electricity expenses. In particular, the degradation and efficiency of the HES and the EV's BESS are discussed. In addition, operating expenses (OPEX) are analyzed in the context of electricity costs for both the building and the vehicle. To increase the comparability of the results, a vehicle with an internal combustion engine (ICE) serves as a reference case.

As illustrated in Figure 1, three different charging strategies for the EV are analyzed and compared: Simple charging (SC) and optimized charging (OC) schemes, which both allow unidirectional power flows from the building to the vehicle, and the vehicle-to-building (V2B) strategy, which is an extension of the OC scheme allowing bidirectional power flows [6,8]. It is known that vehicle usage patterns may vary strongly [9]. For this reason, to make more valid statements about the degradation behavior, efficiency, and OPEX, the vehicle utilization patterns of a commuter and a supplementary vehicle are investigated. These vehicles are characterized by varying plug-in times at the power outlet of the prosumer's residence. As an additional degree of freedom, interaction between the EV battery and an optional stationary HES is examined. Particularly, the influence on the degradation and the efficiency of such a scenario considering two BESSs (EV and HES) is discussed. For the sake of simplicity, throughout this work, a typical German household with corresponding load and PV generator profiles is utilized and price signals of the German energy market are incorporated. However, the methodology can be applied to other profile data and the conclusive results drawn in this contribution are valid for other regions worldwide. An overview of the discussed simulation structure is visualized in Figure 1.

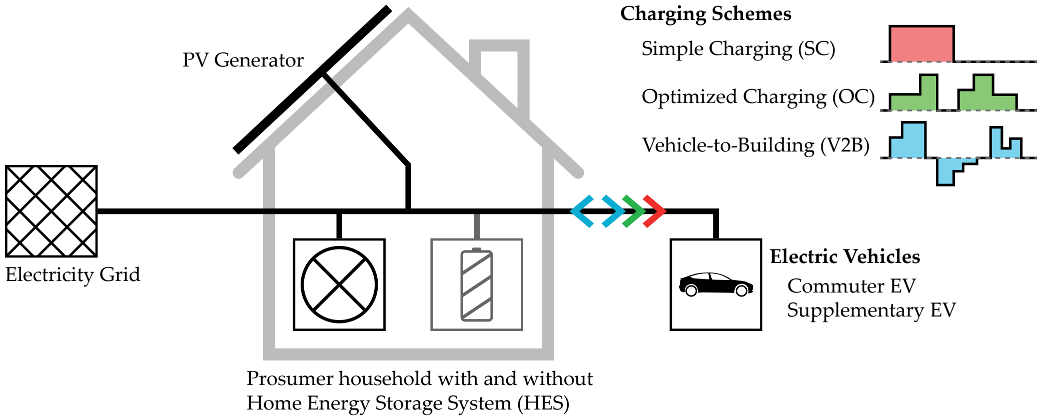

Figure 1. Schematic structure of the simulation environment of a prosumer household with three varying simulation dimensions: Consideration of home energy storage system (HES), two electric vehicle (EV) utilization patterns (commuter and supplementary car), and three different charging schemes (SC, OC, V2B).

The investigated scenarios in this work are simulated using a two-step approach. First, the residential power flow (RPF) model with an underlying linear programming (LP) algorithm optimizes the power flows within the residential multi-node system. Next, the optimized power flows are transferred to the open source simulation tool *SimSES* in order to model the resulting battery degradation and system efficiency [10].

This paper is structured as follows: Section 2 explains the optimization and simulation models as well as the system's topology, Section 3 presents the simulation results, and Section 4 concludes with a summary and discussion.

2. Methods

In order to optimize the electricity exchange between components and analyze the storage systems in a detailed fashion, two solution methods are combined, as is illustrated in Figure 2.

First, the power flows between the individual technical units are optimized using the RPF model. The underlying algorithm is based on LP, derived from the MATLAB optimization toolbox and the Gurobi optimizer [11]. Then, the simulation tool *SimSES* is used, which is capable of simulating the technical parameters of an energy storage system [10]. The results of the linear optimization are transferred to *SimSES* and represent the inputted alternating current (AC) power values of the energy storage system's inverter. By using *SimSES'* integrated operation strategy *PowerFollow*, the predefined time-discrete power values are implemented, and a detailed simulation is carried out. Both tools, the RPF model and the *SimSES* simulations are conducted in MathWorks MATLAB R2018b, operating at a sampling rate of 15 min [5].

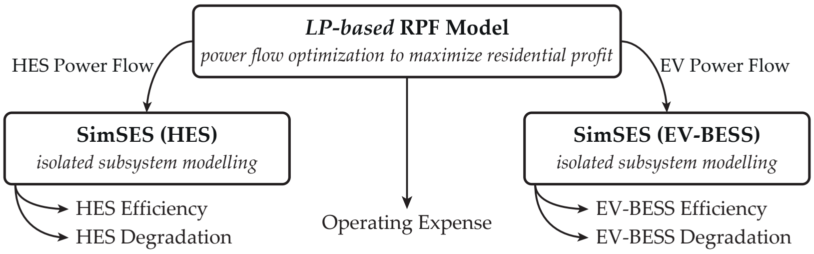

Figure 2. Schematic diagram of the two-step model structure, consisting of a linear programming (LP) based residential power flow (RPF) model, which optimizes the power flows so that the operating expenses (OPEX) are minimized, and the simulation tool *SimSES*, which validates the technical characteristics, round-trip efficiency, and battery degradation of the battery energy storage systems (BESSs).

The profit of a residential electricity prosumer in Germany is computed by simulating several different system configurations: Optional HES, optional EV, three different EV charging schemes, and two vehicle usage patterns.

Depending on the scenario, the RPF model of the investigated household consists of up to six main components, which are illustrated in Figure 3. The household is equipped with a PV generator with 8 kWp peak power, which is a common size for an average German household [12]. The PV generator system is composed of the PV panels, maximum power point tracker (MPPT), and inverter that converts the generator's direct current (DC) power into AC power. The one-year data measured from a PV system installed in Munich, Germany is used as the PV generating profile. To implement the degradation of the PV system, a degradation factor of 0.5% of the PV's peak power per year is assumed [4,13].

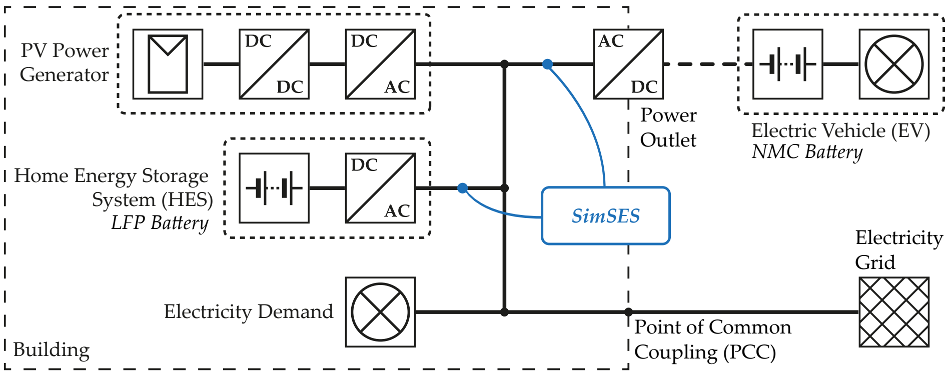

Figure 3. Residential power flow (RPF) model, consisting of the AC-coupled home energy storage system (HES), a photovoltaic (PV) power generator, electricity demand, the power outlet with the connected electric vehicle (EV), and the superordinate electricity grid. The simulation tool *SimSES* is used to validate the technical characteristics of the considered battery energy storage system (BESS).

In order to consider the electricity demand of a typical household, a representative one-year load profile (*profile* 31) out of a freely available set of smart-meter derived household load profiles is used in this study [14]. The annual electricity demand (only of the building, excluding that of the EV) of the considered household is set to 6000 kWh, a value taken from literature and well-suited to an average German household [12].

Further parameters and technical specifications of the household and its stationary HES can be taken from Table 1. The eligibility requirements, according to the German Federal Ministry of Economics and Technology, stipulate a feed-in limitation of 50% for PV generators that are operated in combination with a stationary or decentralized BESS [15]. Furthermore, a fixed feed-in remuneration price of 0.123 EUR/kWh is utilized, which is fixed and guaranteed for a period of twenty years [13]. Due to the projected electricity price of 0.437 EUR/kWh in 2030 and the electricity price of 0.294 EUR/kWh in 2018, a compound annual growth rate (CAGR) of 3.35% is assumed for the electricity purchase price in the simulation [16].

Table 1. Main parameters for the prosumer building and the home energy storage system (HES).

Parameter	Value
Annual electricity demand	6000 kWh [12]
PV peak power	8 kWp [12]
Feed-in limitation	50% [15]
Feed-in remuneration	0.123 EUR/kWh [13]
Initial electricity price	0.294 EUR/kWh [16]
Electricity price CAGR	3.35% [16]
Battery chemistry	lithium iron phosphate (LFP)
Nominal energy content	9 kWh [12,17]
SOC limitation	5%, 95% [12,17]

Lithium ion batteries (LIBs) are assumed for both the EV and HES. The cell chemistry chosen for the stationary HES within the building is based on a lithium iron phosphate (LFP) cathode and graphite anode. This chemistry allows a high cyclic stability [18], which makes it a suitable candidate for stationary applications [17].

The average German household with a HES has a usable energy content of 8.1 kWh [12]. From this the nominal energy content of 9 kWh is derived with the state of charge (SOC) limitations of 5% and 95% [17]. Furthermore, a self-discharge rate of 0.6% of the nominal energy content per month is assumed for the LFP cell [17]. Efficiency losses during charge and discharge processes of the battery are calculated via *SimSES*' equivalent circuit model, which depends on charging and discharging current, battery temperature, and SOC [10].

The semi-empirical degradation model of the LFP cell is also incorporated in *SimSES*. Degradation analysis is based on a superposition of calendar and cycling-related capacity fade [19]. During idle periods only calendar degradation, whereas during load periods also cyclic degradation is occurring [20]. This cyclic degradation is a function of multiple factors, including the depth of cycle (DOC), current, SOC range, and temperature [10]. A constant ambient temperature of 25 °C is assumed throughout the simulation period as the HES is installed within the building.

Since the AC coupling topology is the dominant topology for HESs in Germany [12], this setup is also used in this work. One of the major advantages of this topology over a DC coupling to the PV generator is an easy integration into a building with an existing PV generator, thus ensuring a high level of flexibility [21].

For the power-electronics efficiency, a simplified constant value of 95% is assumed in the RPF model. In order to make more accurate statements about the efficiency of the BESSs, the *SimSES* simulation tool takes into account a concave efficiency curve, which is derived from previous literature [4,22]. This curve considers the dependence on the inverter's output power and the fact that values below 10% of the rated inverter power result in a significantly lower efficiency.

Analogous to the procedure for the stationary HES, the power flows to and from the EV are optimized using the RPF model and then validated in *SimSES*. For all simulations of the EV and the ICE vehicle, a *B-segment* small car is considered [23–25]. An overview of the technical characteristics for the considered vehicles can be found in Table 2.

A nickel manganese cobalt (NMC) based cathode cell chemistry is chosen for the EV's BESS. Compared to other LIB cell chemistries, the NMC cell offers a higher energy density. The nominal and usable energy contents of the chosen EV battery, 21.6 kWh and 18.8 kWh, are closely linked to numbers often stated for EVs widely used in Germany. Derived from the nominal and usable energy contents, SOC boundaries of 8% and 95% are defined [17]. Similar to the LFP cell of the HES, the self-discharge rate of the NMC cell is set to 0.6% of the nominal energy content per month. Both the RPF model and detailed simulations using *SimSES* assume a round-trip efficiency of 95% for the EV battery [26].

In comparison to the highly sophisticated battery model of the LFP cell, the EV's battery is modelled using a more generic approach within *SimSES* [10]. Similar to previous work, a Wöhler curve (i.e., stress-number (S-N) curve) based fatigue model is used as the underlying method to estimate cycling-induced stress in the battery [4]. This method leads to an exponential weighting of DOC, i.e., an increased DOC leads to an overproportional increase in battery stress level, which again results in a reduced amount of equivalent full cycles (EFC) compared to low DOC values; thus, resulting in a shortened battery lifetime [27].

Table 2. Parameters for the electric vehicle (EV) and the internal combustion engine (ICE) vehicle.

Parameter	Value
Vehicle class	B-segment small car [23–25]
Battery chemistry	nickel manganese cobalt (NMC)
Nominal energy content	21.6 kWh [28]
Useable energy content	18.8 kWh [28]
Battery round-trip efficiency	95% [17]
Annually driven distance	13,922 km [29]
Electricity consumption	12.9 kWh/100 km [28]
Fuel consumption	5.3 L/100 km [30]
Initial fuel price	1.45 EUR/L [16]
Fuel price CAGR	2.25% [16]

The annual mileage of a passenger car is based on the German average, which is 13,922 km [29]. Therefore, a comparable EV, which consumes 12.9 kWh/100 km, requires approximately 1800 kWh annually [28]. In this paper, a gasoline-powered vehicle with an average fuel consumption of 5.3 L/100 km is used [30]. Analogous to the electricity costs, a temporally dynamic behavior is also assumed for the fuel price: An initial price of 1.45 EUR/L fuel is assumed for the start of the simulation. Due to the projected gasoline price of 1.89 EUR/L in 2030 and the gasoline price of 1.45 EUR/L in 2018, a CAGR of 2.25% is assumed for fuel prices in the simulation [16].

As part of this work, two EV profiles are created synthetically. The profiles for the two considered EVs (commuter and supplementary vehicle) are based on the US06 driving cycle and 83 charging profiles provided by the Forschungsstelle für Energiewirtschaft e. V., which are used in the federal study *Mobility in Germany* [9,31,32]. Both vehicle utilization patterns consist of a driving profile and a binary time series, which indicates whether the vehicle is connected to the power outlet of the building. It is assumed that the EV is only charged at the residential building and this additional electricity demand is directly allocated to the total electricity consumption of the household.

In Figure 4 an exemplary week (Monday to Sunday) in early summer is illustrated. The dashed areas in the two lower subplots show the plug-in times of the two utilization patterns, where the respective EV is connected to the building. As is immediately apparent, both profiles differ strongly in terms of their total plug-in time and respective daytime behavior: The commuter profile is only rarely connected to the building's power outlet during times of high solar irradiation on weekdays, which makes it more difficult for this vehicle user to directly utilize surplus PV power. Instead, the cumulative plug-in time of the supplementary car is much higher, so the potential of optimizing the power flows between building and vehicle is assumed to be higher.

In order to bring the difference of the vehicle utilization types into a quantifiable context, the quotient between plug-in time and the residual power is formed. Residual power is defined as the difference between PV power and demanded power. For the two types of examined profiles, the resulting correlation coefficients are 7% for the commuter vehicle and 28% for the supplementary car. With the increased plug-in time, the BESS availability of the EV is increased, which increases the degree of freedom for power flow optimization. This increased utilization coefficient leads to a reduction in electricity purchases, which in turn lowers the OPEX of the prosumer. Based on this theory, this metric is introduced and discussed further in the following sections.

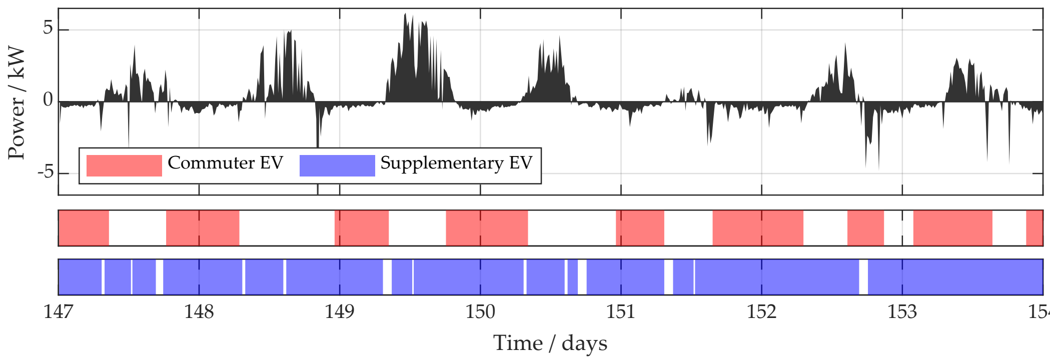

Figure 4. Residual power of exemplary week (Monday to Sunday) where photovoltaic (PV) excess power is characterized by positive values and the associated plug-in times (colored area) of the electric vehicles (commuter EV = red, supplementary EV = blue).

In addition to the two aforementioned vehicle utilization patterns, three different EV charging schemes are introduced. All three strategies are discussed in the context of storage system efficiency, degradation, and economic impact:

- Simple charging (SC): A simple rule-based charging of the EV is applied, where power is delivered unidirectionally from the power outlet of the building to the vehicle. As long as the vehicle is connected to the building and the EV's battery SOC has not reached the maximum SOC limit, the EV gets charged at the maximum allowed charge rate. The RPF model, as well as the simulation tool *SimSES*, are considering constraints for the respective SOC and C-Rate boundaries.
- Optimized charging (OC): Similar to SC the power outlet is used for unidirectional vehicle charging only. An advanced strategy is used that optimizes and controls the amount of energy and the timing of the EV's charging. The controller is fed by input values such as power flows within the building and the plug-in times of the EV.
- Vehicle-to-building (V2B): As an extension of the OC strategy, V2B enables a bidirectional power flow between the EV and building.

The RPF model's objective is to maximize the profit from the electricity sold and purchased throughout the simulation period. This comes down to a minimization of the OPEX of the prosumer. All scenarios use the following base objective function:

$$Max \sum_{i} \left(E_i^{\mathrm{r}} \cdot p_i^{\mathrm{r}} - E_i^{\mathrm{p}} \cdot p_i^{\mathrm{p}} \right) \tag{1}$$

whereby E_i^{r} denotes the amount of electricity that is sold to the superordinate electricity grid at time step i. The purchased electricity per time step is defined by the variable E_i^{p}. The price signals p_i^{r} and p_i^{p} describe the remuneration and purchasing price at time i. Considering changing electricity prices over time, price signals are time-dependent. Besides the objective function, inequality constraints for the BESSs' SOC and C-Rate, as well as equality constraints for the power flows at each node are considered and derived from a previous contribution [33].

Literature shows that the total cost of ownership (TCO) for an EV in Germany depends on many factors [25]. Due to the perennial lifetime of modern BESSs and the complex estimation of future BESS investment costs, capital expenditures (CAPEX) are neglected. In order to make the results as comprehensible as possible, only electricity costs and fuel costs are taken into account.

3. Results

The simulation results are presented and discussed in the following section. In total, fourteen different scenarios are conducted. As shown in Table 3, three different charging schemes, two vehicle usage patterns, and either one or two BESSs within the system are considered. The results are discussed in the context of battery degradation, storage system efficiency, and overall economic assessment, from the perspective of operating expenses for the prosumer.

Table 3. Overview of the fourteen simulated scenarios with three different charging schemes, two vehicle usage patterns, and either one or two BESSs within the prosumer household.

Vehicle Usage Pattern	ICE	ICE w/HES	SC	OC	V2B	SC w/HES	OC w/HES	V2B w/HES
Commuter Supplementary	yes (*ICE*)	yes (*ICE*)	yes yes	yes yes	yes yes	yes yes	yes yes	yes yes

3.1. Economic Assessment of OPEX

As a first metric, the scenarios are evaluated and discussed from an economic perspective. Here, the OPEX for a short-term period of one year and a longer-term ten-year period are considered.

During the first year, even the EV scenario with the highest OPEX, the SC scheme, showed a cost reduction of 31% without HES compared to the ICE vehicle without HES. With the addition of a home energy storage system to the scenarios, the OPEX reduction when using the SC scheme is 39% (EUR 571) in comparison to the ICE vehicle with the same HES.

As illustrated in Figure 5, strong differences between EV charging strategies can be detected. Both without and with HES, the implementation of an optimized charging (OC) scheme leads to a reduction in OPEX. Further cost improvements can be gained by allowing bidirectional power flows (V2B) between the building and the EV. This impact of optimized charging schemes (unidirectional and bidirectional) is particularly strong if there is no additional HES, leading to cost reductions of 14% and 23% in comparison to the SC strategy. The same ratios, with the addition of a HES, are reduced to 12% and 13% respectively.

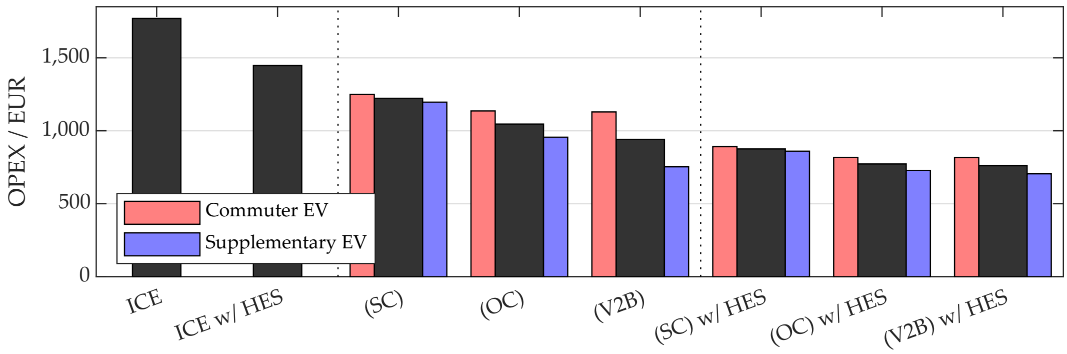

Figure 5. Operating expenses (OPEX) for one year. The dark-grey column represents the average value.

On average, OPEX decrease by 25% if, in addition to an EV, a stationary HES is available, resulting in EUR 115 cost reduction for the observed setting and year. Furthermore, the results for the commuter and supplementary car in the V2B scenario without HES showed a strong difference. Due to the relatively higher plug-in time of the supplementary car (especially during periods of high PV power), more self-generated energy can be stored in the vehicle, which results in higher self-consumption and self-sufficiency rates that are illustrated in Figure 6. Additionally, the scenarios of the supplementary car, with or without an additional HES, result in almost the same costs. Again, the supplementary car's high amount of plug-in time increases the utilization of the vehicle battery, thus making the stationary HES almost obsolete.

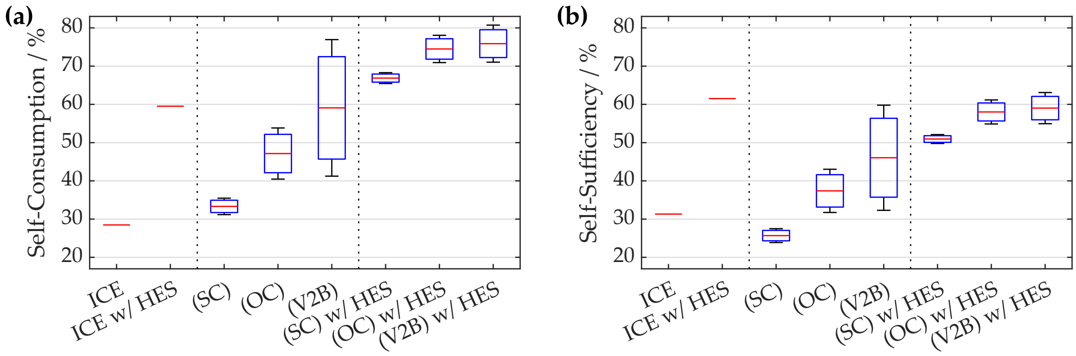

Figure 6. (**a**) Self-consumption and (**b**) self-sufficiency rate for the investigated scenarios. For both metrics, the top edge of each boxplot represents the supplementary car. The lower values of the boxplots are defined by the commuter car, which has a shorter plug-in time compared to the supplementary car.

As shown in Figure 7, the relative differences between the six EV scenarios remain almost the same as in the one-year view. The slight differences are due to the CAGR effect of rising electricity prices. However, the OPEX relationships between the ICE vehicle and EV changed because the expected fuel price increase is lower than that of electricity. A more detailed picture of the OPEX and their seasonal development over ten years can be seen in Figure A1 in the Appendix A.

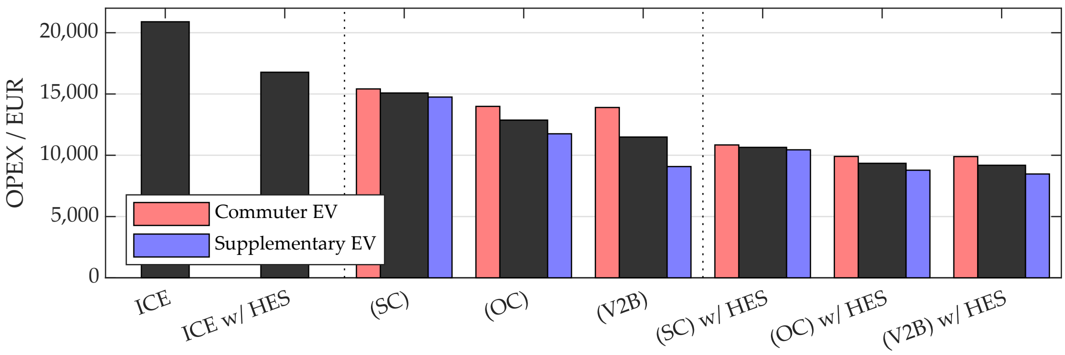

Figure 7. Operating expenses (OPEX) for ten years. Compound annual growth rate (CAGR) of energy costs are considered, so that costs for ten years are more than ten times the one-year costs. The dark-grey column represents the average value.

3.2. Battery Lifetime and Degradation

A common procedure when determining the end of life (EOL) of BESSs is reaching a certain capacity value. Specifically, values between 70% and 80% of the nominal battery capacity are often used to describe the EOL of the BESS [34,35]. In this work, the threshold of 80% is defined as EOL criteria, for both the HES and the EV battery. Figure 8 shows the battery degradation for both BESSs and the simulated scenarios. A more detailed evaluation of the degradation of the two battery types is discussed in the following paragraphs.

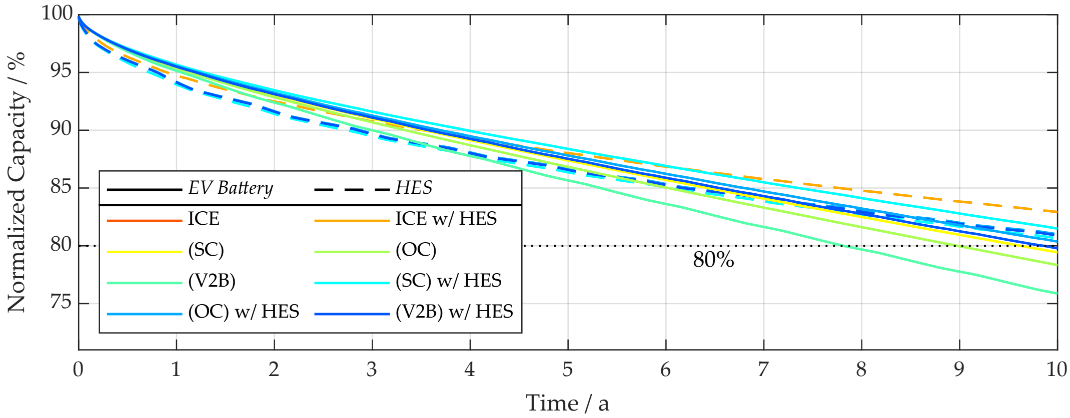

Figure 8. Remaining capacity of electric vehicle's battery (nickel manganese cobalt (NMC) cell chemistry, solid line) and home energy storage system (HES) (lithium iron phosphate (LFP) cell chemistry, dashed line) over ten years, with the highlighted end of life (EOL) threshold at 80% nominal battery capacity.

3.2.1. Home Energy Storage System

As visualized in Figure 9a the results of the observed scenarios show a lifetime between 10.7 years and 13.6 years for the battery of the HES. It is noticeable that the highest lifetime is achieved in the scenario of the ICE vehicle combined with a HES. For the EV scenarios, the lifetime is reduced by about 20%, whereby the simple charging scheme shows the shortest lifespan of 10.7 years. A further trend that can be seen in all three EV scenarios is that the battery lifetime in the scenarios with the supplementary car is always higher than the ones of the commuter vehicle. In both the OC and V2B strategy, this results in a relative lifetime improvement of about 6% for the supplementary car.

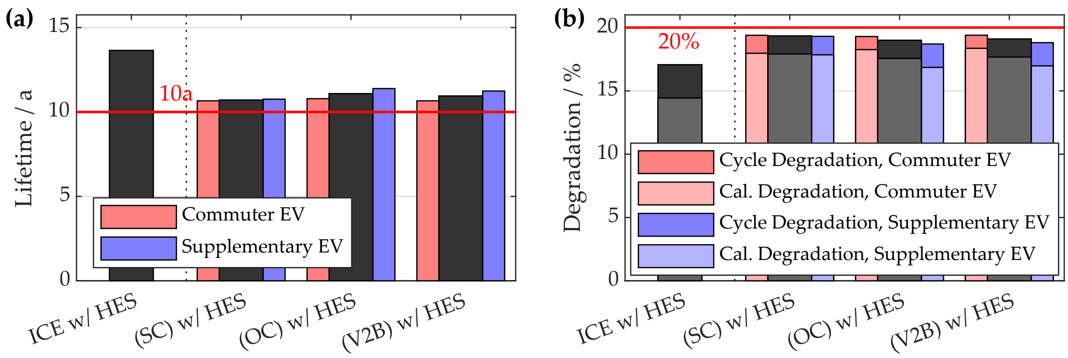

Figure 9. (**a**) Modelled lifetime of the lithium iron phosphate (LFP) home energy storage system (HES) with a nominal capacity of 9 kWh and (**b**) calendar and cyclic degradation during ten years of operation, with the end of life (EOL) condition of 80% remaining capacity. The dark-grey column represents the average value.

In Figure 9b, the relative calendar and cyclic degradation over the course of ten years of operation is illustrated. The results show that the 20% capacity fade is almost reached after ten years for the HES. In Figure 9a, it can be observed that a total lifetime of up to 13.6 years is reached. This can be explained by the initial intensity of degradation processes at the early stage of the battery's operation, which then decrease over time.

The fact that cells suffer particularly from SOC values in the lower and upper SOC range is reflected in the LFP model used for the simulations of this study [20]. Due to increased stress characteristics at these more extreme SOC regions, calendar degradation is accelerated. This, in turn leads to a reduced lifetime. At roughly 90%, calendar degradation processes are the main driver for the reduced battery lifetime. On the other hand, the cyclic degradation stress is fostered by high amounts of EFC. It should also be emphasized that the measured values shown are not the only drivers for battery degradation.

The battery's EFC are especially significant for cyclic degradation. The four HESs of the observed scenarios show annual EFC values of between 167 to 246, as shown in Figure 10a. Especially in the SC scheme, the EFC are significantly higher than those of the other scenarios. The lowest and almost equal amount of EFC is achieved in the settings of unidirectional (OC) and bidirectional (V2B) optimized charging.

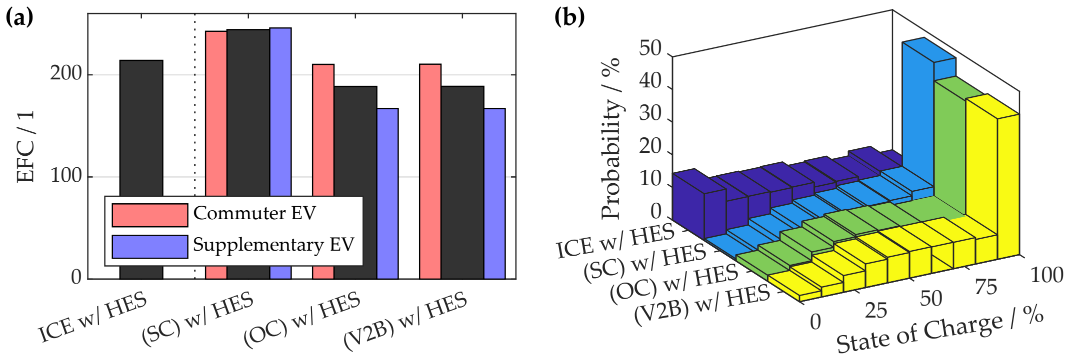

Figure 10. (**a**) Average amount of annual equivalent full cycles (EFC) of the home energy storage system and (**b**) probability distribution of the average state of charge (SOC) per scenario. The dark-grey column represents the average value.

Another degradation factor that is of importance for the lifetime of a LIB is the average SOC. This measure is illustrated in Figure 10b and gives insight into the probability distribution of the SOC for the four considered HESs. Here, a distinctive difference between the ICE vehicle and EV scenarios can be seen. While the SOC values of the HES have a rather homogeneous distribution in the ICE scenario, values in EV settings are much more heterogeneous. In all considered scenarios in which an EV and a HES are combined, it is shown that the SOC of the HES has a high probability density at high values. In the case of the simple charging (SC) scheme, the trend towards high SOC values is particularly strong. As with the number of EFC, here too, both scenarios OC and V2B show approximately the same, and better, results.

3.2.2. EV Battery

Like the evaluation of the HES's data, the battery of the EV is also examined with regard to degradation for the different scenarios. *SimSES* is used to model an isolated storage system behavior of the EV battery. Since the battery model used for the NMC cells is a generic model in comparison to the semi-empirical degradation model used for the LFP cells, results are shown in less detail for the EV battery.

A common standard for the expected lifetime and warranty period for EV batteries is seven to ten years [36]. Within this period, the remaining battery capacity should not fall below the defined EOL criteria of the battery. For the considered scenarios, it is shown that the EV battery has a lifetime of between 7.2 years and 11.8 years, as can be seen in Figure 11.

It is noticeable that its lifetime can be increased by an average of 19% if the EV battery works in conjunction with the stationary HES. The existence of a second storage system leads to a segmentation of the power flows, which results in a reduced stress level of the EV battery.

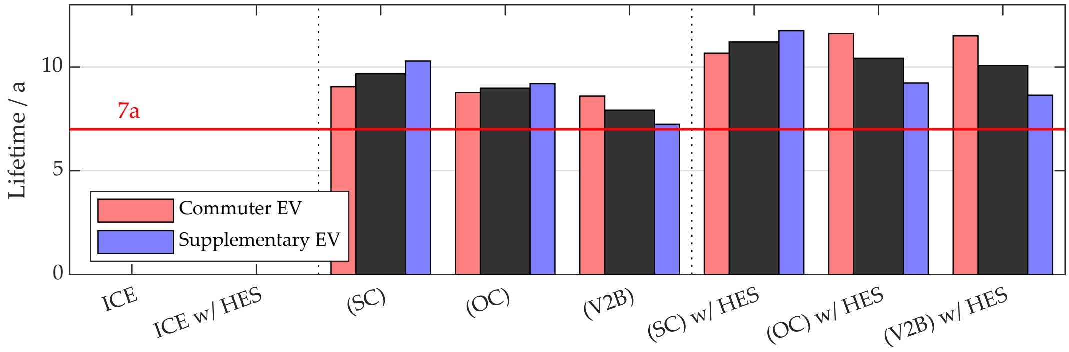

Figure 11. Lifetime calculation of the electric vehicle's nickel manganese cobalt (NMC) battery, based on a generic battery model, with the defined end of life (EOL) condition of 80% of the nominal capacity. The dark-grey column represents the average value.

The scenarios with SC and OC schemes show the same amount of EFC, due to the fact that in these unidirectional scenarios, only the power needed at a later time for driving is delivered from the building to the vehicle. Despite the same amount of EFC of the EV battery in the SC and OC scenarios, the lifetime of the optimized charging (OC) scheme is reduced by 7%. For better interpretation along with the degradation model used herein (based on Wöhler curves), the average absolute values of the DOC are shown in Table 4. Here, it can be seen that the average DOC in scenarios with a HES decreases by about 30% compared to the same settings without a HES.

Table 4. Annual amount of equivalent full cycles (EFC) and the absolute depth of cycle (DOC) (normalized to the amount of EFC) of the battery taken as an average from the commuter and supplementary electric vehicle (EV).

	ICE	ICE w/HES	SC	OC	V2B	SC w/HES	OC w/HES	V2B w/HES
EFC	n/a	n/a	85.5	85.5	119.3	85.5	85.5	89.5
$\overline{\lvert \mathbf{DOC} \rvert}$	n/a	n/a	1.00	0.98	0.98	0.58	0.76	0.76

The degradation in the case of V2B is significantly higher. Results show that the annual number of EFC at 119.3 increase by 40% when there is no additional BESS in the system besides the EV battery. This increase in EFC and the relatively high average DOC values result in a lifetime reduction of about 12% compared to the OC scheme.

For scenarios considering two BESSs, the V2B scenario again shows the highest battery degradation. Because of the permanently available HES, surplus PV power can also be stored in the stationary HES and therefore the number of EFC in the V2B scenario is only slightly higher than that of the unidirectional scenarios (SC and OC). However, the battery lifetime in the V2B case is shortened by about 3% compared to the same setting with OC scheme.

The commuter car battery in the V2B scenarios has a lower energy throughput and thus a lower number of EFC. The relatively higher plug-in time of the supplementary car allows more surplus energy to be charged into and discharged from the EV battery, resulting in a higher number of EFC and a reduced lifetime.

3.3. Storage System Efficiency

In addition to battery degradation, BESSs' round-trip efficiency values are also considered. For both BESS types, the stationary HES and the storage system of the EV, a round-trip efficiency of about 88% is achieved for all operational modes.

More detailed analysis reveals that the dominant source of storage losses comes from power-electronics. This is in line with efficiency analysis conducted on stationary storage systems [37].

Overall, between 8% and 10% efficiency losses are caused by the inverter. This emphasizes the relevance for optimizing the specifications of the technical components of a storage system.

Furthermore, storage losses are considered during the charging and discharging processes of the battery. Storage losses within the battery cells range from 2% to 4% in the considered simulations, which is in line with results from literature [17]. Self-discharge losses, which account for below 0.1% of the total energy throughput, play a subordinate role. This low percentage of storage losses is similar for both storage technologies in all scenarios.

4. Discussion and Conclusions

The following section summarizes the results derived from the simulations and discusses them in the context of previous literature. At the end of the section, related and future research fields are highlighted.

4.1. EV Versus ICE Vehicle

In the previously discussed results section it is shown that an EV can have a significant economic advantage compared to ICE powered vehicles when it comes to reducing electricity costs of a prosumer household. Considering a time span of ten years, it is shown that OPEX can be reduced by an average of 37% (without an additional stationary HES) and 42% (with HES). Even the least economically lucrative scenario with simple charging (SC) shows an average savings potential of 28% (without HES) and 37% (with HES) compared to the same scenarios with an ICE powered vehicle.

Looking at the average results of the individual EV scenarios, it can be said that the considered additional energy costs for the investigated ICE vehicle are about EUR 7400 higher than for its electric-powered counterpart, which may justify an investment in a higher priced EV. Of course, further cost components and economic and policy aspects must be taken into account in order to carry out a complete economic analysis [25,38]. Furthermore, at the moment, there is no consensus on when an EV is equivalent to an ICE vehicle in terms of investment costs.

In the context of battery lifetime, the simulations reveal a trend of stronger degradation when an EV is included in the consideration. The HES's battery reaches the defined EOL criterion earlier by 20%, on average, when an EV is connected to the household. Minimizing OPEX means that more self-generated energy is stored in the HES. In the EV scenarios, the effect leads to an increased occurrence of high SOC levels, which accelerates internal degradation processes of the LFP cells [10]. In order to compensate this effect, the developed charging strategies must be further optimized.

Furthermore, the share of automotive batteries that are used for further applications after their primary use as an EV battery is growing. Particularly, the installation and operation of such second-use batteries in stationary applications is increasing [39]. This use of second-use batteries allows an additional economic impact of the BESS, which makes it more lucrative for their stakeholders [40].

4.2. Impact of Vehicle Utilization Pattern

From the simulations it can be concluded that the supplementary vehicle type has a beneficial effect on electricity cost reductions. This is shown by the lower OPEX in all scenarios when compared to the commuter EV, which has less plug-in time at the building. This relation confirms the initial theory that a higher correlation coefficient between residual power and plug-in time leads to an economic improvement. It is expected that, from the perspective of an office building with PV generation, the connected EVs from commuting employees would have the same beneficial outcome. The underlying effect can also be explained by the household's increased self-consumption and self-sufficiency rate with the supplementary vehicle profile [7]. On average, OPEX in the commuter car scenarios are about 16% higher than those with the supplementary vehicle. This cost increase is particularly high when considering a bidirectional charging scheme (V2B).

In terms of battery degradation, on the other hand, it is shown that battery lifetime of the HES is slightly increased in the commuter car scenarios. However, the average battery lifetime for the

EV battery shows a favorable behavior in the supplementary scenarios, in particular during V2B charging schemes. DOC values and the underlying Wöhler curve for the EV battery degradation model represent the main drivers for this effect [27].

4.3. Impact of Considering an Additional HES

Previous literature has shown that it is still difficult to operate a HES in Germany in an economically lucrative way [4]. Although the results presented in this paper only relate to OPEX, it is noteworthy that a HES can reduce these costs by an average of 23% during the first year. When taking into account the rising electricity retail tariff estimated for the next ten years [16], the cost savings may rise by another few percentage points.

Due to the segmentation of power flows when considering a HES, both the energy throughput and relative DOC values of the EV battery can be reduced. The reduced stress level leads to an increase of the EV's battery lifetime by an average of 20%.

Whether and to what extent the advantages of the lifetime extension of the EV battery and OPEX reduction justify additional expenses of a HES depend, in turn, on the CAPEX. Taking into account the discussed prosumer and an operation period of ten years, HES investment costs below EUR 2305 (V2B scenario) and EUR 4437 (SC scenario) would be justified. The higher value in the SC scenario results from the fact that, here, an additional HES has a higher potential for OPEX improvement, which is further discussed in the subsequent paragraphs. Assuming steadily declining CAPEX for stationary battery packs [41], a HES can become increasingly interesting for residential buildings. If, in addition to the minimization of OPEX and self-consumption improvements, other applications are served, the economics of the HES can be increased even further [42].

4.4. Impact of Charging Scheme

Both in the scenarios with and without HES, the simple charging (SC) scheme resulted in the highest OPEX. The condition that the EV is charged as soon as it is connected to the building also results in overall low self-consumption and self-sufficiency rates of 33% and 26%, which are illustrated in Figure 6.

In the optimized charging (OC) scheme with a HES, the electricity costs can be reduced by 12% (about EUR 1300 for a ten-year operation period). This effect is even more pronounced when there is no additional HES and the EV battery is the only BESS in the setting. OPEX can be reduced by 15% (about EUR 2200) compared to the SC scheme when the EV battery is the only storage unit to decouple energy supply and demand.

By allowing a bidirectional power flow between the building and the EV (V2B) instead of the unidirectional power flow (OC), further cost savings can be achieved. Relative to the OC scheme, this results in a further OPEX reduction of 2% (with HES) and 11% (without HES). Analogous to the above comparison between the SC and OC schemes, there is an increased cost saving potential if the EV battery is the only storage unit in the system. When considering the absolute values of the savings potential, an OPEX reduction of EUR 160 (with HES) and EUR 1381 (without HES) results for an operation period of ten years. This comes at the cost for additional upfront investment costs: The low savings potential of the scenario with HES suggests that the additional investment costs for a power outlet with bidirectional power flow are difficult to compensate. On the other hand, in scenarios with a single EV battery, the V2B scheme could be economically lucrative in comparison to the OC scheme, if the additional investment costs are below the cost savings of EUR 1381.

In contrast to improved electricity expenditures, the lifetime of the EV battery decreases in the OC and V2B schemes. Due to increased energy throughput, particularly in the V2B scheme, the lifetime is reduced by up to 12% compared to the optimized unidirectional charging (OC). SC scenarios lead to the highest lifetime with a relative improvement of 7% compared to the OC scheme. One of the main drivers for the increased degradation are the relatively higher DOC values in the OC and V2B scheme. In addition, two more obstacles come into play: The prediction of power values is needed for effective OC and V2B schemes. Furthermore, automotive original equipment manufacturers (OEMs) provide warranties on the use of the EV battery for vehicle purposes. While this is maintained in the SC and OC schemes, the EV battery in the V2B scheme does not only function as an EV battery, but also as a buffer storage unit for the whole prosumer household. Thus this could pose a challenge to incentivizing V2B schemes.

The EV market shows a trend towards increasing battery capacity. EVs being manufactured currently are often more than twice as large in terms of nominal energy content than the 21.6 kWh EV battery that is considered in this work. It can be expected that the higher cost savings and the lower necessity of an additional HES due to the V2B scheme will be enhanced with these increased capacities.

4.5. Limitations and Future Research

The discussed simulations are conducted assuming perfect foresight of energy supply and demand, both for the household and the vehicle. In order to emphasize on limited foresight, other algorithms can be used. For instance, in [43] a fuzzy logic controller (FLC) is presented for a V2B environment.

Since the discussed RPF model is using constant efficiency values, it would be an improvement to implement non-linear relationships, as already implemented in *SimSES* [10]. This step would improve the RPF's validity, but would also lead to an increasing complexity of the optimization algorithm, resulting in an elevated computation time.

Although the generic battery model of the NMC cell provides values for the battery degradation [4,27], the quality of the battery model can be improved further. In comparison to the current model, more sophisticated degradation models could be implemented, as done for the semi-empirical degradation model of the LFP cell [20].

In order to generate a more profound insight into the economic results of the discussed settings, further research should take additional cost components into account. Although it is not clear how the CAPEX for batteries will develop in the future, there are estimations in recent literature that could be used [41]. Another cost component that is of relevance in that perspective are battery degradation costs [44]. The consideration of these factors would provide a more complete picture of the total cost of ownership (TCO), which in turn would allow for more precise conclusions.

Author Contributions: S.E. developed the conceptualization, including the generation of the optimization framework for the residential power-flow model, coordinated the study, and wrote the manuscript. H.H. significantly contributed to the conceptualization and methodology of the study. D.K. offered support in using simulation tool SimSES. A.J. provided overall guidance for the study and contributed to fruitful discussions on the methodology. All authors have read and approved the manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating current
BESS	Battery energy storage system
CAGR	Compound annual growth rate
CAPEX	Capital expenditures
DC	Direct current
DOC	Depth of cycle
EFC	Equivalent full cycles

EOL	End of life
EV	Electric vehicle
HES	Home energy storage system
ICE	Internal combustion engine
LFP	Lithium iron phosphate
LIB	Lithium ion battery
LP	Linear programming
NMC	Nickel manganese cobalt
OC	Optimized charging
OPEX	Operating expenses
PV	Photovoltaic
RPF	Residential power flow
SC	Simple charging
SOC	State of charge
V2B	Vehicle-to-building

Appendix A

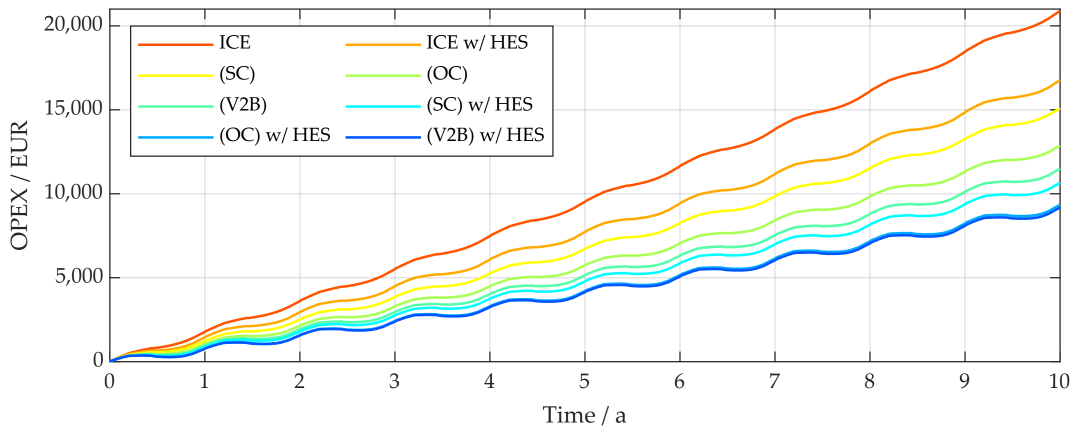

Figure A1. Operating expenses (OPEX) during ten years of operation showing a strong seasonal pattern.

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4 Flexibility provision of a multi-storage cluster

Building on Section 2.4.2 and Chapter 3, the following chapter introduces the publication titled *Evaluating the interdependency between peer-to-peer networks and energy storages: A techno-economic proof for prosumers*. In the publication, the *multi-storage* context is considered on the one hand within households, but also within a community of multiple residential entities. The focus is on energy management and the use of flexibilities in the energy system. Home storage systems and EVs are considered as sources of flexibility in the study. As presented in Chapter 3, the charging strategies of EVs are also discussed in this study. The empirical study, considering 38,892 different scenarios and combinations of households, utilizes an integrated approach, where the EMS operation and the peer-to-peer trading (cf. Section 2.2) is conducted simultaneously. Doing so, both the flexibility provision from the energy storage systems and the trading within the community can be optimized together and the utilization of synergies is increased.

To perform the study, a linear programming model, *flex_opt*[3], is designed and integrated into the MPC framework together with appropriate degradation models (NMC cells for the EV battery and LFP cells for the home energy storage). Although degradation awareness constraints are considered in the optimization to account for excessive energy throughput through the storage devices, the detailed modeling of battery cell degradation are calculated based on literature [238–240]. For the evaluation of the studies, the modeled households are also equipped with PV generators in the different scenarios. To investigate their impact on the community, the penetration rate of the technical units (PV, EV, and home energy storage) is varied. Since the focus of the study is on the performance of the EMS and peer-to-peer trading, the decision-making process, specifically the decision to provide flexibility, is of crucial relevance.

The paper compares the decentralized and central decision-making approaches. The reference case without a local electricity market is used as a benchmark. As shown in Section 2.4.2, the substantial distinction between decentralized and central decision-making is that the decentralized approach only has the information and decision-making power over a single household. Because in the decentral approach the information of the other households is not known, a household can only optimize its own flexibility deployment as it is not informed of nor can react to the decisions of other peers. For the local electricity market, only the net surplus or demand is traded between peers in the decentralized approach. In the central approach, on the other hand, a central unit (the central or community EMS) knows all relevant data of the energy system and can optimize the power flows and the provision of flexibility throughout the community. Especially for smaller communities of less than twenty households, the results show that both the centralized and the decentralized approach can lead to significant reductions in electricity costs per household. This is because locally traded electricity is exchanged between the peers and thus, less electricity must be purchased externally from electricity providers. By co-optimizing flexibility provision and electricity trading in the community, the central approach can increase the economic added value for the community and its households more effectively than

[3] Code is publicly available at the Gitlab repository: `https://gitlab.lrz.de/open-ees-ses/flex_opt`

the decentralized approach. However, the higher use of flexibility also comes at a cost; represented by the changes to the operating strategy of the EV battery, leading to a reduction in its lifetime. In comparison, the decentralized approach shows no change in lifetime of the energy storage systems, as the optimization on the household level does not lead to a change in flexibility provision.

The coordinated integration of the EMS and peer-to-peer trading provides an important technical proof for practical implementations. The results also make a significant contribution towards increasing customer participation, a crucial element of success for any peer-to-peer network. The two options presented in the paper allow for the catering to different user values, which should increase acceptance and proliferation of local electricity markets with various flexibilities. For instance, the centralized approach is advantageous when participants value independence from electricity retailers, whereby a decentralized approach may be preferable to a community where households want to keep control over their flexibilities.

Author contribution Stefan Englberger developed the idea of the study, developed the linear programming and model predictive control framework, carried out the simulations, and analyzed the data. Tariq Almomani helped to parameterize the model. Holger Hesse helped to develop the model and guided its development. Archie Chapman, Wayes Tushar, and Tariq Almomani helped to analyze the data. The manuscript was written by Stefan Englberger, Archie Chapman, Wayes Tushar, and Stephen Snow and was edited by Holger Hesse, Andreas Jossen, and Rolf Witzmann. All authors discussed the data and commented on the results.

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Evaluating the interdependency between peer-to-peer networks and energy storages: A techno-economic proof for prosumers

Stefan Englberger[a,*], Archie C. Chapman[b], Wayes Tushar[b], Tariq Almomani[c], Stephen Snow[b], Rolf Witzmann[c], Andreas Jossen[a], Holger Hesse[a]

[a] Institute for Electrical Energy Storage Technology, Technical University of Munich, Arcisstr. 21, 80333 Munich, Germany
[b] Faculty of Engineering, Architecture and Information Technology, University of Queensland, St Lucia, Brisbane, QLD 4072, Australia
[c] Associate Professorship Power Transmission Systems, Technical University of Munich, Arcisstr. 21, 80333 Munich, Germany

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ABSTRACT

The rapid decentralization of energy generation and storage facilitates an opportunity to redesign existing energy systems. Here, peer-to-peer energy trading in local markets offers advantages for demand response and flexibility of energy delivery, yet it still faces problems of customer acceptance, namely, concerns over sharing control of batteries and the degradation impacts of increased cycles. To help overcome these hurdles, this research develops a techno-economic model that optimizes the interplay between peer-to-peer trading and energy management systems in a community. The model distinguishes between two decision making approaches in a local electricity market: decentral, where the household retains full control over its storages, and central, where the flexibilities are fully leveraged to maximize the community benefit. Both approaches demonstrate the significant monetary benefit of peer-to-peer trading, with the central approach reaching the greatest profitability potential. Negative effects on the battery lifetime only occur in the central case with bidirectional vehicles, and the degradation is comparatively slight.

1. Introduction

Power networks, and distribution networks in particular, are facing operational and planning challenges from rising levels of customer investment in distributed generation, storage and flexible loads, collectively called distributed energy resources (DER). For instance, the installed rooftop capacity of photovoltaic (PV) systems globally has grown from 8 GW in 2007 to over 400 GW in 2019 [1], and annual added battery capacity from private electric vehicle (EV) sales is projected to increase from 170 GWh in 2019 to between 1.2 and 2.6 TWh per year by 2030 [2]. Consequently, members of the community who used to be passive consumers of the electricity network are becoming prosumers – consumers who also produce electricity [3] – and are expected to play key roles in deciding how the future power systems will evolve and operate. The change in prosumers' roles within the distribution network present significant challenges to power network operators, who face daytime minimum demand challenges due to prosumers' solar export to the network [4] and the peak demand problems owing to EV ownership [5]. One potential way to address these challenges is to enable prosumers to interact among themselves and trade electricity with one another [6] – also known as peer-to-peer (P2P) trading.

P2P trading is a prosumer-centric energy sharing scheme in which prosumers in a power network can share a part of their resources, such as electricity [7], storage space [8], and negawatts [9], and information with one another to attain certain objectives. It is important to note that although existing power network regulatory regimes do not allow P2P trading to occur in the today's electricity markets, extensive pilot trials around the world [10] and government initiatives to reform the electricity sector [11] are moving towards a future where P2P trading will be integrated into the broader electricity market.

Furthermore, P2P trading has several positive characteristics, including relatively low computational and implementation overheads [12], the ability to engage extensive user participation [13], reductions in energy cost [14], and balancing local generation and demand [15] by enabling secured trading [16]. P2P trading empowers both the prosumers [17] and community managers [18] that are trading within a community, which makes it a suitable candidate to operate within future customer-focused regulatory regimes [19]. As such, research over the last five years has established P2P as an indispensable element of the future electricity market, considering its potential to benefit participating prosumers and provide useful services to other stakeholders [10]. However, to the best of our knowledge, there are still no large-scale

* Corresponding author.
E-mail address: stefan.englberger@tum.de (S. Englberger).

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Nomenclature

CEMS	community energy management system
DER	distributed energy resource
EFC	equivalent full cycle
EMS	energy management system
EV	electric vehicle
HEMS	home energy management system
HES	home energy storage
P2P	peer-to-peer
PV	photovoltaic

Parameters & variables

$\mathbb{C}^{\mathrm{electricity}}$	economic cost for electricity
$\mathbb{C}^{\mathrm{deg}}$	economic cost for battery degradation
$\mathbb{C}^{\mathrm{inv}}$	economic cost for battery investment
$\mathbb{C}^{\mathrm{tra,loc}}$	economic cost for locally traded electricity
$\mathbb{C}^{\mathrm{tra,ret}}$	economic cost for electricity taded with the retailer
$\mathrm{EFC}^{\mathrm{exp}}$	expected EFC until the battery's end-of-life
E^{act}	actual energy content of battery
$E^{\mathrm{demand,local}}$	locally traded energy demand
$E^{\mathrm{demand,retail}}$	energy demand traded with the retailer
E^{demand}	energy demand
$E^{\mathrm{EV,act}}$	actual energy content of EV battery
$E^{\mathrm{EV,buf}}$	buffer energy at the EV
$E^{\mathrm{EV,CH,ext}}$	external charging energy at the EV
$E^{\mathrm{EV,CH}}$	charging energy at the EV
$E^{\mathrm{EV,DCH}}$	discharging energy at the EV
$E^{\mathrm{EV,dri}}$	energy demand for driving at the EV
$E^{\mathrm{EV,SD}}$	self-discharge energy at the EV
$E^{\mathrm{HES,act}}$	actual energy content of HES battery
$E^{\mathrm{HES,CH}}$	charging energy at the HES
$E^{\mathrm{HES,DCH}}$	discharging energy at the HES
$E^{\mathrm{HES,SD}}$	self-discharge energy at the HES
E^{Load}	energy consumption
E^{nom}	nominal energy content of battery
E^{PV}	energy provided by the PV generator
$E^{\mathrm{supply,local}}$	locally traded energy supply
$E^{\mathrm{supply,retail}}$	energy supply traded with the retailer
E^{supply}	energy supply
$E^{\mathrm{trade,local}}$	locally traded electricity
$E^{\mathrm{trade,retail}}$	electricity traded with the retailer
$E^{\mathrm{trade,total}}$	total traded electricity
ϵ	share of locally traded electricity
$\eta^{\mathrm{EV,CH}}$	charging efficiency of the EV
$\eta^{\mathrm{EV,DCH}}$	discharging efficiency of the EV
$\eta^{\mathrm{HES,CH}}$	charging efficiency of the HES
$\eta^{\mathrm{HES,DCH}}$	discharging efficiency of the HES
N	set of households
n	household
ϕ	peer's economic incentive to trade locally
$P^{\mathrm{EV,CH,ext}}$	external charging power at the EV
$P^{\mathrm{EV,CH}}$	charging power at the EV
$P^{\mathrm{EV,DCH}}$	discharging power at the EV
$P^{\mathrm{EV,max}}$	maximum (dis)charging power of the EV
$P^{\mathrm{HES,CH}}$	charging power at the HES
$P^{\mathrm{HES,DCH}}$	discharging power at the HES
$P^{\mathrm{HES,max}}$	maximum (dis)charging power of the HES
$\mathrm{p}^{\mathrm{purchase,retail}}$	retailer's purchase price for electricity
$\mathrm{p}^{\mathrm{sell,retail}}$	retailer's sell price for electricity
$\mathrm{SOC}^{\mathrm{EV,max}}$	maximum SOC of EV battery
$\mathrm{SOC}^{\mathrm{EV,min}}$	minimum SOC of EV battery
$\mathrm{SOC}^{\mathrm{HES,max}}$	maximum SOC of HES battery
$\mathrm{SOC}^{\mathrm{HES,min}}$	minimum SOC of HES battery
$\mathrm{SOC}^{\mathrm{preference}}$	SOC threshold for reserve energy
T	set of time steps
t	time step
x^{plugged}	binary variable, defining if vehicle is connected

development of P2P trading that is ready to be deployed in today's electricity market. The reason could be partially attributed to the fact that prosumers are more interested to use their DER such as batteries to go off-grid and become energy-neutral, rather than interacting with other stakeholders within the network, as found in [20].

A study of 268 prosumers who were asked about battery purchases reported that 70% of the survey respondents purchased their batteries to reduce personal electricity costs with intensions to less interact with other stakeholders of the network [20]. Two important factors that have motivated their decision in separating themselves from any form of interaction are (i) the fear of losing the ability to control their assets [21] and (ii) the concern about the reduction of the lifetime of their resources due to their extensive usage for the local market support [22]. These place technology developers, network operators, and policymakers in a conundrum, as the success of P2P trading and other smart energy infrastructure, relies on the proactive participation of prosumers [23], and therefore, prosumers' reluctance to share their assets can negatively impact the lived experience of P2P energy trading [22].

To this end, this paper provides empirical evidence to close two gaps in existing literature. Firstly, we incorporate the prosumer's home energy management decision-making process into the subsequent decision to trade on the local P2P market. We present an integrated P2P energy trading algorithm that empowers prosumers to use an energy management system to control their energy resources and optimally meet their home energy demand and then, whenever appropriate, share the surplus in the local P2P market. By doing so, prosumers' uncertainty of losing control of their energy assets is eliminated. Secondly, using extensive data from a Germany-based pilot trial, we demonstrate that the extra charging and discharging cycles of prosumers' batteries due to P2P trading has minimal effect on battery lifetime.

In summary, the main contributions of the work are:

- The impacts of peer-to-peer energy trading on energy storage systems are analyzed via a novel matching mechanism for coordinating home energy management and peer-to-peer trading.
- We compare the financial performance and degradation effects of our decentralized P2P matching mechanism to a centralized approach that optimizes the overall techno-economic outcome, considering both stationary and mobile energy storages.
- The first evidence of the minimal impact on battery lifetime as well as the shared techno-economic benefits to the prosumer due to P2P trading.
- This paper examines the interaction between home energy management and P2P trading, providing a crucial technical demonstration to help overcome the techno-economic and social challenges.

The remainder of the paper is structured as follows. Section 2 introduces the methodology of analysis, P2P framework, and its mathematical formulation. The results of our analysis are presented in Section 3, discussed in Section 4, and concluded in Section 5.

2. Methods

2.1. Decentralized versus central decision making approach

We differentiate between two approaches for the energy management of households in a P2P network, as illustrated in Fig. 1. In both

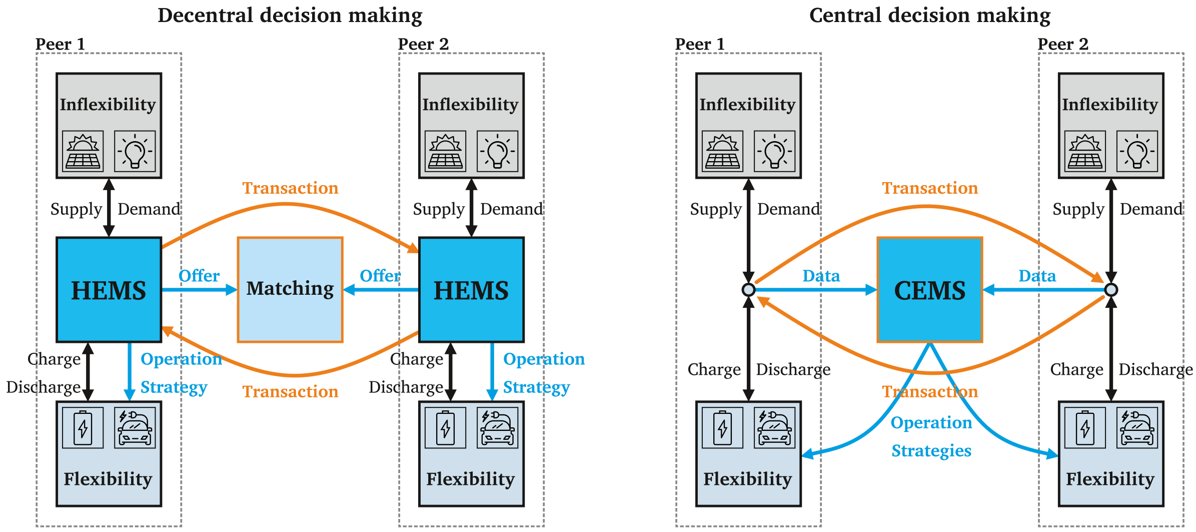

Fig. 1. Schematic illustration of decentralized and central decision making in a peer-to-peer (P2P) network. Each peer is characterized by its energy inflexibilities and flexibilities. The inflexibilities represent the supply and demand stemming from producing and consuming components. Stationary and mobile energy storages allow the flexible charging and discharging of electricity, enabling the temporal shift of supply and demand. There are two decision making approaches to calculate the offers, transactions, and operation strategies of the peers: decentralized (left) and central (right). For the decentralized approach a HEMS at each peer calculates the offers and transfers them to the matching platform of the P2P network. With the larger information base and flexibility pool, the CEMS simultaneously calculates the optimal operation strategies for all flexibilities and peers to yield the optimal techno-economic outcome.

approaches, each household contains inflexibilities, such as its electricity base demand and the supply of PV generators, as well as flexibilities, which allow for a temporal shift of supply and demand. The EMS utilizes the expected energy values from demand and supply to calculate an optimal operation strategy for the flexibilities and the techno-economic optimum for electricity demand and supply offers. Here, as shown in Eq. (1), the sum of the peers' demand and supply matched locally ($E^{\text{demand,local}}$ and $E^{\text{supply,local}}$ respectively) must be equal:

$$\sum_{n\in N} E_{n,t}^{\text{demand,local}} = \sum_{n\in N} E_{n,t}^{\text{supply,local}} \tag{1}$$

For any supply and demand unfulfilled in the local market, the electricity is cleared with the retailer.

The decentralized and central decision making approaches differ in four main ways: type of EMS, information availability, computation complexity, and market mechanism. In the decentralized approach, each peer has its own home energy management system (HEMS), whereas a central authority or community energy management system (CEMS) determines the optimal operation strategies for all households in the central approach.

To enable the central decision making, the CEMS has access to the demand and supply data, as well as system states of the flexibilities, from all peers. It also has the capability to control and operate the flexibilities in the network to maximize the P2P community's techno-economic potential. The peers have no access to data from the other households in the network. The market mechanism determines how offers are matched in the local market. Whilst offers are non-binding, once matched, these transactions between peers are binding and must be delivered.

In the decentralized approach, on the other hand, offers are determined by the HEMS and then transferred to the clearing and matching. If both demand and supply offers exist during a given trading interval, they are cleared on a community level to reach the highest share of locally traded electricity. This highest share is defined as the minimum value of the total offered demand and supply on a community level, as it is shown in Eq. (2). After the clearing, the offers are matched with respective counterparts following a 'fairness policy' (illustrated in Fig. 2). The fairness policy ensures that each received offer is considered in the matching and that the volume matched is calculated based

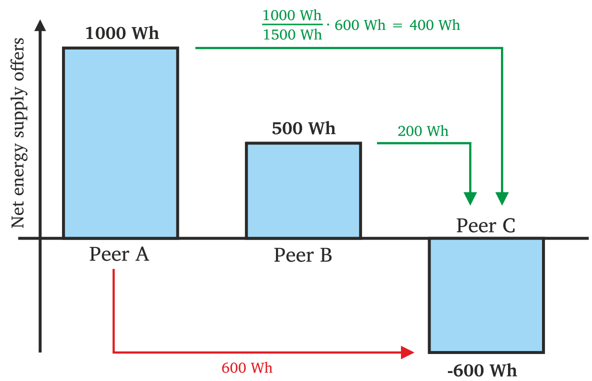

Fig. 2. Exemplary illustration of the fairness policy in a peer-to-peer (P2P) market with offers from three peers. Peers A and B have positive net energy supply offers. Although peer A could meet the full demand from peer C, this would not be fair towards peer B. With the fairness policy all offers in the P2P community are considered for the creation of binding transactions.

on the weighted offer volume (cf. Eqs. 3 and (4) for demand and supply respectively). After clearing and matching, the offers are converted into transactions and transferred to the respective peers. Every peer needs to know which offers became transactions on the P2P market, as well as the volume, timing, and counterpart of electricity transaction. In the central approach, the energy management and matching occur simultaneously. Therefore, the offers are directly converted to binding transactions and the operation strategies for all peers are calculated simultaneously.

$$\sum_{n\in N} E_{n,t}^{\text{trade,local}} = \min\left\{ \sum_{n\in N} E_{n,t}^{\text{demand}}, \sum_{n\in N} E_{n,t}^{\text{supply}} \right\} \tag{2}$$

$$E_{n,t}^{\text{demand,local}} = \frac{E_{n,t}^{\text{demand}}}{\sum_{n\in N} E_{n,t}^{\text{demand}}} \cdot \sum_{n\in N} E_{n,t}^{\text{trade,local}} \tag{3}$$

$$E_{n,t}^{\text{supply,local}} = \frac{E_{n,t}^{\text{supply}}}{\sum_{n\in N} E_{n,t}^{\text{supply}}} \cdot \sum_{n\in N} E_{n,t}^{\text{trade,local}} \tag{4}$$

2.2. Assessing the financial benefit

In our methodology, the benefit of P2P trading is characterized by ϵ, the proportion of electricity supplied or demanded in the network that is traded locally (Eq. (5)). The total traded electricity, either by household or on a community level, $E^{\text{trade,total}}$, is defined in Eq. (6) as the sum of electricity traded with other peers ($E^{\text{trade,local}}$) and with the electricity retailer ($E^{\text{trade,retail}}$).

$$\epsilon = \frac{E^{\text{trade,local}}}{E^{\text{trade,total}}} \tag{5}$$

$$E^{\text{trade,total}} = E^{\text{trade,local}} + E^{\text{trade,retail}} \tag{6}$$

In Eq. (7), ϕ represents the individual peer's incentive to trade locally in Euro. A prerequisite for the design of a local market with more favorable trading conditions than offered by the retailer is a price gap between the retail purchase and sale prices $\mathrm{p}^{\text{purchase,retail}}$ and $\mathrm{p}^{\text{sell,retail}}$. This price difference emerges in markets with demand-pull policies subsidizing decentralized production of electricity, where feed-in-tariffs are declining and where the retail price remains high, because risks of price fluctuations are covered by the retailer. The welfare gained due to local trading on a community level is equal to the gap between the two price signals. In our approach, this economic gain is divided equally between the peers – both the local supplier and consumer – so that the incentive to either supply or purchase local electricity is equal for both. As a result, the unit ϕ, allows us to draw general conclusions regarding the financial benefit per peer in a local market, isolating the effect of the specific underlying tariff structure, which differs with federal and state regulations.

$$\phi = \frac{\mathrm{p}^{\text{purchase,retail}} - \mathrm{p}^{\text{sell,retail}}}{2} \tag{7}$$

From a mathematical point-of-view, the incentive to trade electricity locally arises as soon as a price corridor exists. In our approach, the midpoint of the price corridor (average between $\mathrm{p}^{\text{purchase,retail}}$ and $\mathrm{p}^{\text{sell,retail}}$), is set as the static local market price. With this straightforward and simple approach, computation complexity is reduced significantly. Also, the individual incentive to trade locally, ϕ, is the same for all peers. The offers and transactions consist of electricity values and the prices for traded electricity are equal and homogeneous for all peers. This eliminates the likelihood of market manipulation and arbitrage opportunities.

$$\begin{aligned}\mathbb{C}^{\text{electricity}}_{n,t} = \; & E^{\text{demand}}_{n,t} \cdot \mathrm{p}^{\text{purchase,retail}} - E^{\text{supply}}_{n,t} \cdot \mathrm{p}^{\text{sell,retail}} \\ & - E^{\text{trade,local}}_{n,t} \cdot \phi \end{aligned} \tag{8}$$

In the P2P network, the individual households' electricity costs, $\mathbb{C}^{\text{electricity}}$, are given by Eq. (8), where E^{demand}, E^{supply}, and $E^{\text{trade,local}}$ denote the total electricity demanded, supplied, and traded locally by the household. The first term calculates the electricity costs, as if the full demand is covered by the retailer. If the household is a prosumer, these costs are compensated by revenues from electricity sold to the retailer (second term) and if the household participates in a local market ($E^{\text{trade,local}} > 0$), to more favorable conditions, the costs are reduced by the incentive to trade locally, ϕ.

2.3. Mathematical formulation

The developed EMS is based on a linear optimization problem that minimizes the electricity costs of the households and the P2P community. Written in the MATLAB environment, it utilizes the Gurobi solver, which offers advantages in computation performance [24].

$$\min z^{\text{dec}} \quad z^{\text{dec}} = \sum_{n\in N} \sum_{t\in T} \left(\mathbb{C}^{\text{tra,ret}}_{n,t} + \mathbb{C}^{\text{deg}}_{n,t} + E^{\text{EV,buf}}_{n,t} + E^{\text{EV,CH,ext}}_{n,t} \right) \tag{9}$$

$$\min z^{\text{cen}} \quad z^{\text{cen}} = \sum_{n\in N} \sum_{t\in T} \left(\mathbb{C}^{\text{tra,ret}}_{n,t} + \mathbb{C}^{\text{tra,loc}}_{n,t} + \mathbb{C}^{\text{deg}}_{n,t} + E^{\text{EV,buf}}_{n,t} + E^{\text{EV,CH,ext}}_{n,t} \right) \tag{10}$$

Eqs. 9 and (10) show the objective functions of the decentralized and central decision making approaches respectively. Mathematically, these differ only in one respect. While the decentralized EMS minimizes the electricity costs from trading electricity with the retailer ($\mathbb{C}^{\text{tra,ret}}$) only, the central CEMS also minimizes the electricity costs electricity shared within the local network, $\mathbb{C}^{\text{tra,loc}}$. This additional minimization lever is attainable, because the CEMS has access to all offers placed in the market, whereas in decentralized control each EMS only knows what is occurring within one household.

Besides the maximization of the profit from sharing and trading electricity the electricity retailer and with peers in the network, Eqs. 9 and (10) also minimize the cost for cell degradation of the batteries, $\mathbb{C}^{\text{deg}}$. Thus, degradation awareness is introduced to the model. Defined in Eq. (11), the cost of cell degradation is calculated using the flexibilities storage energy throughput, or equivalent full cycles (EFC) and the estimated opportunity costs per battery cycle $\frac{\mathbb{C}^{\text{inv}}}{\text{EFC}^{\text{exp}}}$ [25]. The EFCs are derived from the change in the state of charge over time (cf. Eq. (12)). With this active degradation awareness in place, the algorithm only utilizes a battery if the financial benefit exceeds the costs of degradation.

$$\mathbb{C}^{\text{deg}}_{n,t} = \text{EFC}_{n,t} \cdot \frac{\mathbb{C}^{\text{inv}}}{\text{EFC}^{\text{exp}}} \tag{11}$$

$$\text{EFC}_{n,t} = \frac{|E^{\text{act}}_{n,t} - E^{\text{act}}_{n,t-1}|}{2 \cdot E^{\text{nom}}} \tag{12}$$

$E^{\text{EV,buf}}$, which is also applied in Eq. (13), incentivizes the optimization algorithm to retain a minimum state of charge (SOC) in the EV batteries reserved for driving when the vehicle is connected ($x^{\text{plugged}} = 1$). Due to the constraint formulation, the reserve SOC ($\text{SOC}^{\text{preference}}$) is not applied when the vehicle is not connected, allowing the full energy content to be used for mobility purposes. This minimum state of charge is important to the vehicle owner's peace of mind, as they might need to take a spontaneous, unplanned trip. Guaranteeing this flexibility in this model increases user acceptance [26]. $E^{\text{EV,CH,ext}}$ enables that external charging – outside of the home – is possible but discouraged by significantly less favorable conditions. Thus, the algorithm, avoids external charging when possible.

$$E^{\text{EV,nom}} \cdot \text{SOC}^{\text{preference}} \cdot x^{\text{plugged}}_{n,t} \le E^{\text{EV,act}}_{n,t} + E^{\text{EV,buf}}_{n,t} \tag{13}$$

In addition to the objective functions, to allow real world discussions and analysis, several constraints are implemented. The most important of which are described here. Firstly, there is an energy conservation constraint for every HES and EV battery (cf. Eqs. 14 and (15) respectively). E^{act} hereby represents the actual energy content of the battery and E^{CH} as well as E^{DCH} are the corresponding energy values that are charged and discharged to and from the battery. Due to efficiency losses during charging and discharging the corresponding efficiency values η^{CH} and η^{DCH} are implemented. Ongoing energy losses due to self-discharge are represented by E^{SD}. Besides the energy conservation constraint for the HES, the EV's constraint also considers $E^{\text{EV,CH,ext}}$, which represents the energy that is charged into the EV battery externally (not at the household and not in the community). The last variable, $E^{\text{EV,dri}}$ represents the energy that is consumed during driving.

$$\begin{aligned} E^{\text{HES,act}}_{n,t} = \; & E^{\text{HES,act}}_{n,t-1} + E^{\text{HES,CH}}_{n,t} \cdot \eta^{\text{HES,CH}} \\ & - E^{\text{HES,DCH}}_{n,t} \cdot \frac{1}{\eta^{\text{HES,DCH}}} - E^{\text{HES,SD}}_{n,t} \end{aligned} \tag{14}$$

$$\begin{aligned} E^{\text{EV,act}}_{n,t} = \; & E^{\text{EV,act}}_{n,t-1} + (E^{\text{EV,CH}}_{n,t} + E^{\text{EV,CH,ext}}_{n,t}) \cdot \eta^{\text{EV,CH}} \\ & - E^{\text{EV,DCH}}_{n,t} \cdot \frac{1}{\eta^{\text{EV,DCH}}} - E^{\text{EV,dri}}_{n,t} - E^{\text{EV,SD}}_{n,t} \end{aligned} \tag{15}$$

Further constraints are included in the optimization algorithm. For instance, Eq. (16), which is the node constraint and ensures the energy conservation within each household. Therefore, all incoming energy flows must be equal to the outgoing energy flows. Other constraints

Table 1
Model parameters for the optimization algorithm, home energy storage system, electric vehicle (EV), and EV battery.

Parameter	Value	UOM	Parameter	Value	UOM
General			State of charge limitations	[5,95]	% [33]
Sample time	0.25	h [33]	Battery efficiency	99	% [39]
Optimization period	24	h [25]	Inverter efficiency	95	% [33,39]
Rolling horizon	12	h	Self discharge	0.6	%/month [33,39]
Entities	1–50		Battery invest	800	EUR/kWh [27]
Annual electricity consumption	3500*	kWh [34]	Cell temperature	25	°C [25]
PV peak generation	10**	kWp			
Feed-in limit	70	%[35]	**Electric vehicle & EV battery**		
Grid charges	0.0739	EUR/kWh [36]	Cell chemistry	NMC	[40]
Distribution charges	0.0706	EUR/kWh [36]	Average consumption	189	Wh/km [40]
Electricity surcharges	0.1573	EUR/kWh [36]	Annual driving distance	13 600***	km [41]
Subsidized remuneration	0.0845	EUR/kWh [37]	Nominal energy content	65	kWh [40]
Non-subsidized remuneration	0.0280	EUR/kWh [38]	State of charge limitations	[4,96]	% [40]
Home energy storage system			Preferred minimum SOC	35	% [26]
Cell chemistry	LFP	[33]	Rated active power	11	kW [40]
Nominal energy content	7	kWh [33]	(Dis-)charging efficiency	89.4	% [42]
Rated active power	3.5	kW [33]	Self discharge	0.6	%/month [33,39]
			Battery invest	200	EUR/kWh [27]

* The values are normally distributed with a standard deviation of 500. ** The values are normally distributed with a standard deviation of 1. *** The values are normally distributed with a standard deviation of 1500.

ensure compliance with the technical limitations of the energy storages. For the HES and EV respectively, Eqs. 17 and (18) apply to the state of charge and Eqs. 19 and (20) ensure that the maximum charging and discharging power is not exceeded. For the EV, $P^{\mathrm{EV,DCH}}$ is set to zero if the bidirectional charging is not permitted in the examined case and Eq. (20) ensures that the charging and discharging power remains zero if the vehicle is not connected ($x^{\mathrm{plugged}} = 0$).

$$E^{\mathrm{demand,local}}_{n,t} + E^{\mathrm{demand,retail}}_{n,t} + E^{\mathrm{PV}}_{n,t} + E^{\mathrm{HES,DCH}}_{n,t} + E^{\mathrm{EV,DCH}}_{n,t} = E^{\mathrm{supply,local}}_{n,t} + E^{\mathrm{supply,retail}}_{n,t} + E^{\mathrm{Load}}_{n,t} + E^{\mathrm{HES,CH}}_{n,t} + E^{\mathrm{EV,CH}}_{n,t} \quad (16)$$

$$E^{\mathrm{HES,nom}} \cdot \mathrm{SOC}^{\mathrm{HES,min}} \leq E^{\mathrm{HES,act}}_{n,t} \leq E^{\mathrm{HES,nom}} \cdot \mathrm{SOC}^{\mathrm{HES,max}} \quad (17)$$

$$E^{\mathrm{EV,nom}} \cdot \mathrm{SOC}^{\mathrm{EV,min}} \leq E^{\mathrm{EV,act}}_{n,t} \leq E^{\mathrm{EV,nom}} \cdot \mathrm{SOC}^{\mathrm{EV,max}} \quad (18)$$

$$P^{\mathrm{HES,CH}}_{n,t}, P^{\mathrm{HES,DCH}}_{n,t} \leq P^{\mathrm{HES,max}} \quad (19)$$

$$P^{\mathrm{EV,CH}}_{n,t}, P^{\mathrm{EV,CH,ext}}_{n,t}, P^{\mathrm{EV,DCH}}_{n,t} \leq P^{\mathrm{EV,max}} \cdot x^{\mathrm{plugged}}_{n,t} \quad (20)$$

2.4. Model predictive control

At specified time intervals the optimization algorithm is executed. This model predictive control approach allows the re-evaluation of previous optimizations based on updated input data [25]. In our framework, the optimization horizon for the EMS is 24 hours to follow a full day-and-night cycle. With each new evaluation of the optimization, the algorithm is fed with updated data that lies further in the future to determine the optimal operating strategy for all flexibilities and to calculate the best offers for every household. These offers and transactions for future time steps are permitted and, once made, must be considered in future evaluations of the EMS.

In this simulation, perfect foresight information is used for electricity demand, PV generation, and EV usage patterns. However, in a real world application, these input profiles would be prediction values underlying uncertainty. To deal with the inherent uncertainty, the rolling horizon can be adjusted according to the quality of the prediction data. Thus, the strength of the model predictive control comes into play, and already optimized operation strategies are reevaluated with each update of prediction values.

2.5. Battery degradation models

We differentiate between two cell chemistries in this contribution. For the HES, a battery cell technology with a lithium-iron-phosphate (LiFePO4) cathode is applied, which is a suitable and widely used cell chemistry for stationary storages due to its high cycle stability [27]. Due to the requirement to use battery cells with a high energy density in mobile applications [28], for the EV, established cells with lithium-nickel-cobalt-manganese-oxide (LiNiCoMnO2) cathode material are used [29]. To consider both, calendar [30] and cycle [31] degradation processes within the two different cell technologies with graphite anodes, specific degradation models are applied. The calculation for the capacity fade in both models is examined via the battery cells' physical conditions: lifetime, temperature, voltage, and current [29]. Because of nonlinear degradation mechanisms and battery safety conditions at lower state of health levels, the end-of-life for the stationary and mobile batteries was defined as 80% [32].

2.6. Design of simulations and input data

The results of this study are based on 1903 different parameter sets (cf. Table 1). For each of the scenarios, six use cases are simulated with varying market schemes – reference (no local market), decentral, and central – and EV connection schemes – unidirectional and bidirectional. The network size ranges from one to 50 households [1:1:10,15:5:50] and the penetration rate of the technical equipment – PV generators, HES, and EV – varies between zero to one hundred percent [0%:20%:100%]. With these scenario variations, 38,892 households, 25,928 PV generators, 12,964 home energy storages, and 19,446 EVs are simulated for each case. The data and code for this study is available upon release of the paper.

For the optimization framework four profile sets are used. The energy demand of the household is derived from one-year real measurement data of German households [43]. In addition, the generation profiles from the photovoltaic (PV) generator is derived from one-year real measurement data of a PV system installed in Munich, Germany [33]. The necessary profiles for the electric vehicle (EV) are derived from the Python tool *emobpy* [44]. From *emobpy* the two profile sets for the electricity consumption during driving and the availability time series at the household were used to conduct the study. Computational time strongly varied with the complexity of the optimized case, lying between three and 20 minutes per annual optimization case (on an Intel i7-7600U processor and 16 GB RAM).

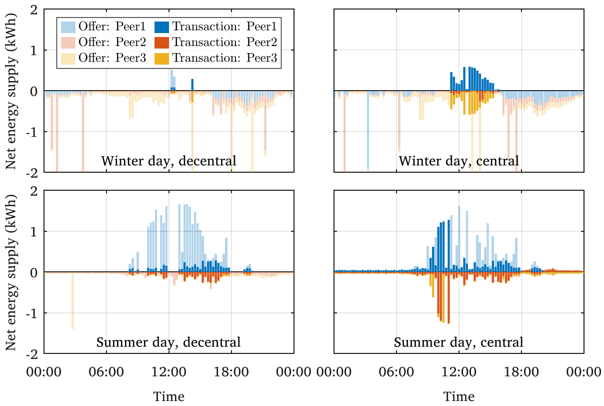

Fig. 3. Comparison of the net energy supply of a peer-to-peer network with three peers using a decentralized (left) and central (right) decision making approach. The top two figures show the results for an exemplary winter day and the bottom two figures for a typical summer day. The peers' offers (pastel colors) for both approaches differ, as the flexibilities are utilized differently on a peer level. It can be seen that the transactions (bright colors) for three peers are more dominant in the central approach. In both approaches, peer 1 (blue) predominantly acts as an electricity supplier whereas peers 2 (red) and 3 (orange) act as net-consumers. Offers that are not matched in the local electricity market are traded with the electricity retailer. Due to the higher coexistence of supply and demand in summer, the locally traded energy is also significantly higher in this season.

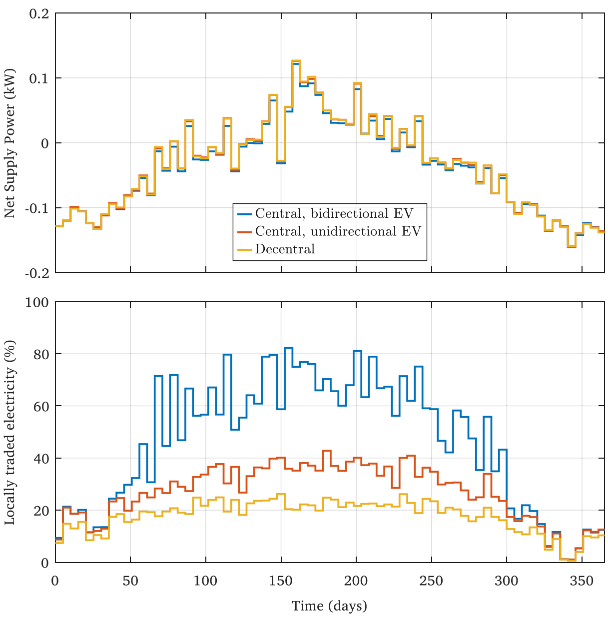

Fig. 4. The net supply power (top) of an exemplary scenario throughout a calendar year represents the net supply offers of an average peer within a local energy market. A clear increase during summer months shows the underlying effect of seasonality. The difference of the net supply power between the three cases comes from the different utilization of the flexibilities (energy storages) on a peer level. The share of locally traded electricity (bottom) distinguishes between the influence of seasonality and the effects of the network's chosen decision making approach and electric vehicle (EV) operation scheme. Particularly during times of electricity surpluses, the central approach shows great economic advantages.

3. Results

We develop an optimization framework to evaluate the techno-economic effects on peer profitability and storage degradation within a P2P network. Our model comprises two main components: (i) the prosumer peers and their assets, and (ii) the coordination mechanism.

Prosumers have inflexible load and PV generation profiles, as well as sources of flexibility, in the form of stationary and mobile storages. Following [33] and [45], two EV connection schemes are considered: (i) unidirectional, in which the vehicle is charged only, and (ii) bidirectional, the vehicle can discharge to the building or grid (i.e. vehicle-to-X). Prosumers' equipment penetration rates for PV, HES, and EV in the network vary across the scenarios. Although the parameters and input profiles are oriented around German households, the model can be applied to any region that has feed-in-tariffs schemes.

The technical objective of this work is to derive and validate a P2P trading platform where local electricity can be traded, so that the heterogeneity between peers increases the profitability for both the individual peer and the community as a whole, and reduces their collective reliance on energy imported from the bulk grid. The coordination mechanism we develop is a P2P training model, based on a matching procedure. Specifically, in this local energy market, all players can submit surplus energy supply or demand in the form of offers. Once cleared and matched with complementary offers, these become binding transactions. We consider two decision making approaches, decentralized and central. In the decentralized case, every household has a home energy management system (HEMS) that determines the offers made to the local energy market. In the central case, one community energy management system (CEMS) determines the offers for all households.

As a baseline, we also consider a reference case, in which a household's power flows are optimized by the HEMS, but there is no local electricity market available for trading with peers.

3.1. *Demonstration of peer-to-peer market mechanism*

Our demonstration examines 1903 simulated scenarios that explore the influence of decentralized and central decision making for the energy management, at different levels of prosumer PV, HES, and EV penetration. To begin, we illustrate the rationale behind the coordination framework and the P2P mechanism, by considering results for an example network with three peers. These are given in Fig. 3, which shows the net energy supply in the form of the peers' offers and transactions. This figure demonstrates that the offers in the decentralized and central approaches differ only slightly on the same winter or summer day, but significantly more transactions are made in the central case. This is explained by the superior information and greater optimization scope of the CEMS, which can utilize the flexibilities across prosumers to optimize the benefit for the entire community. In contrast, the HEMS' available information and optimization scope is limited to one household and its flexibilities only. The benefit of the decentralized approach is that the participating households are not required to give the control of their flexibilities over to a central authority, nor share their supply and demand information. In addition, significantly more net supply is offered to the local market on a summer day than in the winter, due to the seasonal nature of PV generation, which results in a greater share of locally traded electricity in the summer (cf. Fig. 4 and Fig. 5).

We quantify the effects of the market mechanisms on a typical summer day in Table 2, which shows the key metrics for each peer in the reference, decentralized, and central cases. Across the three cases, the inflexible loads and PV generation are identical. The results show that the share of locally traded electricity is more than twice as high in the central case than the decentralized case, while the absolute cost reduction for both the decentralized and central cases is significant.

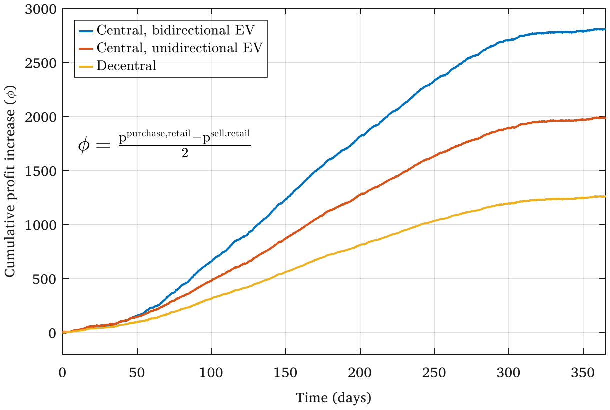

Fig. 5. Average profit increase of a peer within an exemplary scenario. The profit increase determines the economic added value compared to the same setting if no local energy market exists. Particularly during times of electricity surpluses of the peers' profit increase due to the local energy network shows high growth rates. ϕ represents the monetary incentive per peer to trade electricity locally.

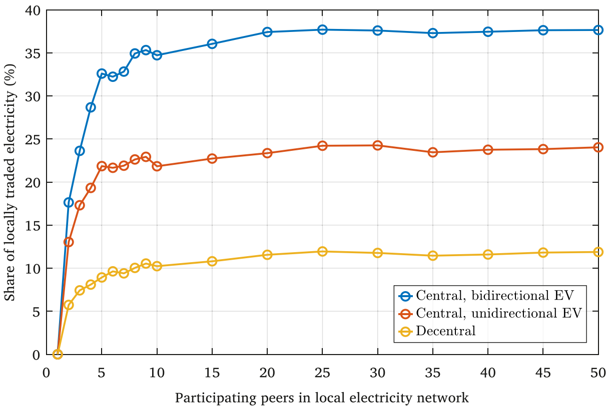

Fig. 6. The annual share of locally traded electricity in a peer-to-peer network by number of participating peers shows a saturating effect as the heterogeneity of peers declines with increasing network size. Scenarios differ in the decision making approach (central vs. decentral) and electric vehicle (EV) charging scheme (uni- vs. bidirectional).

3.2. Financial benefit of peer-to-peer trading

Building on the energy flow results, our financial results show that the benefits to individuals participating in a local P2P market are substantial, especially when decisions regarding the trading amount and trading partners are managed by a CEMS. Fig. 6 shows that the share of locally traded electricity increases strongly up to a network sizes of ten peers. There is a saturating effect up to 20 households, after which the share of locally traded electricity remains stable. This means that the marginal benefit per new peer is neither increasing nor decreasing; that is, constant returns to scale. This is a significant finding, because it shows that a community of twenty or more peers has no disadvantage in allowing additional participants to join the local energy market. Furthermore, the peers' incentive to form local markets is shown to be strong, even for small network sizes. The heterogeneity of households is the key especially in small communities, as offers are more likely to be matched when the inflexibilities of the households are dissimilar. With an increasing network size, it becomes more difficult to maintain heterogeneity, as the likelihood for similarities between the peers also rises.

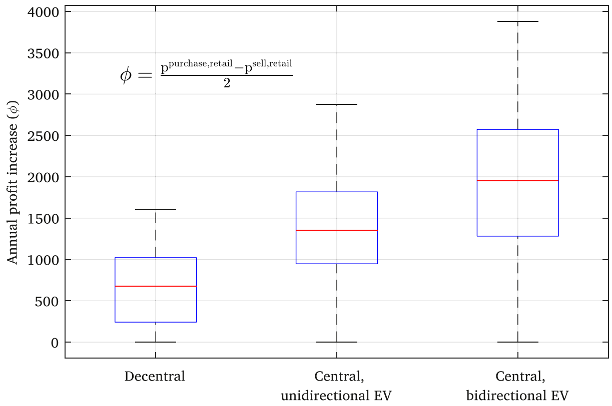

Fig. 7. Annual profit increase due to local peer-to-peer trading. The profit increase determines the economic added value compared to the reference case, where no local energy market exists. ϕ represents the monetary incentive per peer to trade electricity locally. The scenarios (n=1,903) were examined using different decision making approaches (central vs. decentral) and electric vehicle (EV) charging schemes (uni- vs. bidirectional).

As the share of locally traded electricity increases, the profitability on a community and peer level rises proportionally due to the preferable trading conditions on the local market. This monetary benefit per peer is measured in units of ϕ, the added value per kWh traded locally, as shown in Fig. 7. The local electricity price equals the midpoint of the gap between the electricity retailer's purchase and selling prices and forms the incentive for all peers to first trade locally. The central decision making by a CEMS yields the highest monetary benefit, because the authority to define the actions of all peers simultaneously enables the full exploitation of given heterogeneity and flexibility. Further improvements can be reached with bidirectional charging schemes for the EV, as the pool of flexibilities available to the community is expanded when the vehicles are permitted to discharge to the network. If the reference case (without P2P network) is already relatively profitable, i.e. in scenarios with high flexibility penetration, the potential for further profitability improvements through P2P trading declines.

3.3. Degradation costs of peer-to-peer trading

This article aims to provide empirical evidence on the financial and technical merits of local P2P market participation. Besides the need for a financial advantage, the concern of potential participants over reduced battery lifetimes due to P2P trading – especially where a central authority controls the peers' flexibilities – also needs to be assuaged.

Fig. 8 shows the distribution of the battery lifetimes for the EVs and HESs to compare the degradation effects of the decision making approaches. For cases with unidirectional EVs, the battery lifetime of both the stationary and mobile storages is extended in the central approach. This is highly significant, and explained by the lower average state of charge values in the central case, which positively affect the cell chemistries' calendar degradation. With bidirectional EVs, the battery lifetime of the HES is prolonged further in the central case, whereas that of the EV is reduced. Still the central bidirectional case consistently outperforms in terms of monetary benefit. The higher degradation results from the increased utilization of the EV batteries and corresponding rise in energy throughput and cycle degradation. Also, the transformation of EVs from flexible loads in the unidirectional case to bidirectional flexibilities, shifts energy throughput from the HES to the mobile storages. Significantly, due to the degradation awareness integrated in the model, the EMS considers the opportunity costs of energy throughput;

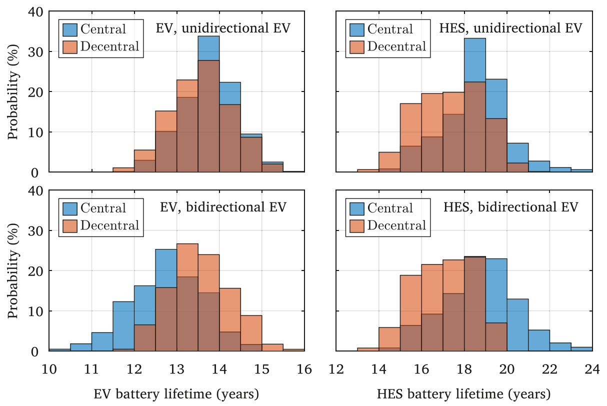

Fig. 8. Absolute change in battery lifetime of home energy storage (HES) and electric vehicle (EV) battery until reaching the end-of-life at 80% remaining capacity, compared to the reference scenario. For all scenarios, the reference case without local electricity market and the decentralized approach show very similar lifetime. In comparison to the other approaches, the central approach yields higher battery lifetimes for the HES, both in uni- and bidirectional EVs cases. The dark red areas depict the overlap of the two cases. For the EV battery lifetime the central approach shows a slight increase for unidirectional operated vehicles and a reduction in battery lifetime for the bidirectional use case. (n_{EV}=19,446, n_{HES}=12,964).

Table 2
Techno-economic results of an exemplary peer-to-peer (P2P) network with three peers and different market schemes for one summer day. The variation between the net demand of inflexibilities and offers comes from the charging and discharging of available flexibilities. Transactions represent the local offers that are matched within the community. The net electricity costs consider both the costs and revenue earned from trading electricity in the local P2P market and with the electricity retailer. The net electricity costs represent the costs minus the revenues from trading electricity. Negative values refer to the revenues that exceed the costs.

	Net supply (kWh)			Locally traded	Net electricity costs (EUR)	Absolute cost reduction (EUR)
	Inflexibility	Offer	Transaction			
P1	31.7	27.2			-0.58	
P2	-7.0	-7.0			0.53	
P3	-3.9	-4.0			0.30	
Reference	**Σ 20.8**	**Σ 16.2**			**Σ 0.26**	
P1	31.7	27.2	4.4	16%	-0.70	0.12
P2	-7.0	-7.0	-3.6	52%	0.43	0.10
P3	-3.9	-4.0	-0.8	20%	0.28	0.02
Decentral	**Σ 20.8**	**Σ 16.2**	**Σ 0.0**	**Ø 29%**	**Σ 0.02**	**0.24**
P1	31.7	24.6	12.8	52%	-0.85	0.28
P2	-7.0	-8.0	-8.0	100%	0.38	0.15
P3	-3.9	-4.8	-4.8	100%	0.22	0.08
Central	**Σ 20.8**	**Σ 11.9**	**Σ 0.0**	**Ø 84%**	**Σ -0.25**	**0.51**

thereby ensuring that the costs of the increased battery utilization are outweighed by its benefits.

There are no significant negative effects due to P2P trading when the decentralized approach is applied. This is explained in Fig. 9, which shows the same utilization of flexibilities in the reference and decentralized approaches. The only difference between the reference and decentralized case is that the latter trades electricity in the local P2P market before sending unmatched offers to the retailer, and the former only trades with the retailer. As a result, the stationary and mobile storages have the same degradation behavior with and without P2P trading when using a decentralized approach.

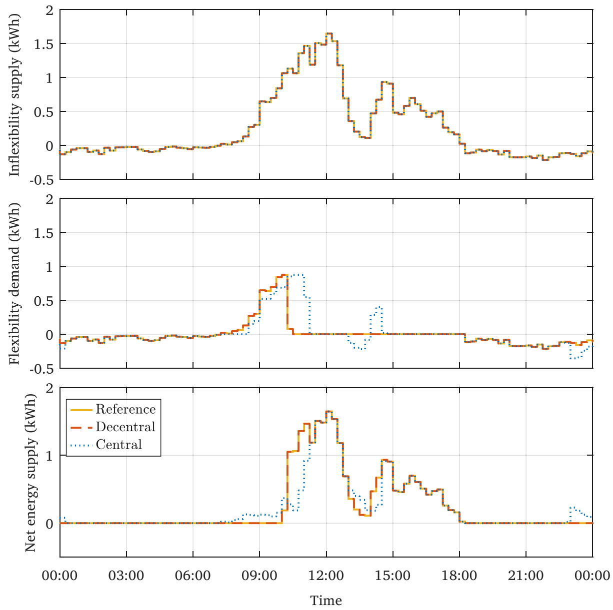

Fig. 9. Comparison of the three operation approaches – reference (no local market), decentral, and central – for the energy management system based on an exemplary day. The inflexibility energy supply (top) for all cases is the same. The flexibility demand (middle), to charge and discharge the storages, for the central approach differs from the other two approaches. Due to the equal utilization of the flexibilities, the reference and decentralized approach have the same net energy supply (bottom).

4. Discussion

Achieving the potential of this work involves addressing the social challenges of gaining user trust and acceptance [20]. Based on negative user experiences when P2P trading algorithms are opaque to users [22], we recommend that the local market designers make the mechanisms as simple, straight-forward, and transparent as possible. When market designs use dynamic price signals, arbitrage opportunities arise that are tempting to the sophisticated trader. However, to a risk averse prosumer household, the resulting complexity creates uncertainty whether they will be the winner or the loser of a trade. Our approach uses a fixed profit margin, equally distributed between trading parties. This way, it is easy for the participants to understand the benefit of trading, which will subsequently increase the likelihood of the households being convinced to participate. For policy makers who are interested in boosting the integration of renewables and the autarky of local grids, the authors recommend drafting policies that reduce or eliminate network charges and taxes on electricity traded between peers in a local market. This will further accelerate the proliferation of local P2P networks.

Despite the significant strengths, the results of this paper are limited by some assumptions. Firstly, the input profiles and parameters reflect German regulations. Secondly, network surcharges were neglected in favor of simplicity. Though these would reduce the magnitude of the trading incentive when deducted from the retail price corridor, the resulting behavior and share of locally traded electricity would not be influenced, as long as an incentive to trade locally remains. However, the published method can be applied to any region with a tariff structure and appropriately adjusted to reflect any existing surcharges. The scope of this article does not include effects on the electricity network, where storage and P2P trading [46] and network operator-coordinated battery dispatch [47] have been shown to contribute positively. Instead, we focus on P2P market approaches, with the community and its households as the primary stakeholders. Further research can build upon our findings and explore the resulting effects on distribution grids and the distribution system operator's interests in local electricity markets.

As the central approach optimizes the benefit of the whole community, situations can arise where an individual household could be disadvantaged for the sake of the community. However, in over 99.99% of cases, this disadvantage is only momentary and outweighed by the advantages offered during a one year time period. The algorithm is not designed to prohibit that an individual can be placed at a disadvantage, as this would limit the degrees of freedom of the optimization. The threat, though negligible, of being put at a longer-term disadvantage might serve to prevent participation. Thus, it is extremely important that the business model or agreement implemented by the peers clearly defines how the generated community profit is distributed so that any provision of flexibility is remunerated appropriately. The large variety of possible business model designs and their realizations in practice present a fascinating area for further research.

5. Conclusions

Proof that the network benefits of peer-to-peer can be achieved with negligible degradation of customer assets is vital to the social acceptance that underpins such schemes. Our results provide empirical evidence for the techno-economic benefits that are possible with peer-to-peer trading when combined with home or community energy management systems. The strength of this model arises from the incorporation of 1903 scenarios, 38,892 households and consideration of specific battery cell chemistries. We show that the strongest financial potential is reached when a central authority controls the flexibilities in the network and electric vehicles are bidirectional. There are no reduced battery lifetimes in the central approach when electric vehicles are unidirectional, however, with bidirectional electric vehicles, peers need to take into account that the greater utilization of the electric vehicle battery comes at the cost of increased cycle degradation. For decentralized peer-to-peer markets, results show that local electricity trading does not affect battery lifetimes. We do not conclude which approach – central or decentral – is superior, instead evaluate their respective advantages and disadvantages. Depending on local conditions and participant preferences, market makers can apply these results and design a peer-to-peer trading market that best reflects participants' values. For instance, if independence from the electricity retailer and financial profit is prioritized in the local society, the central approach will offer a strong incentive to participate. Alternately, if participants are unwilling to share data with or cede control over their flexibilities to a central authority, the decentralized approach may foster greater acceptance and participation.

We suggest three priorities for future work necessary to realize the peer-to-peer benefits modelled by our findings: (i) This current modelling is based on the German energy market. Future work should seek to generalize the benefits of both approaches to other comparable markets, e.g. US, UK. (ii) Incentivizing customer participation is central to the success of any peer-to-peer network. Our study suggests two options suitable to cater for different user values in a specific deployment context, e.g. the desirability of a centralized approach if users value independence from electricity retailers, versus a decentralized approach which may be more favorable to a community who values control over their flexibilities. Prior to implementation, economic modelling should be complemented by social research targeting user values and local drivers of smart energy technology adoption. (iii) While beyond the scope of this present paper, further work is also vital into the effect of both approaches on grid operation and distribution systems. Bidirectional charging can be problematic for local grid management when deployed at scale and this effect should be modelled prior to implementation.

Declaration of Interests

The authors declare no competing interests.

CRediT authorship contribution statement

Stefan Englberger: Conceptualization, Validation, Writing – original draft, Methodology, Funding acquisition. **Archie C. Chapman:** Validation, Writing – original draft. **Wayes Tushar:** Writing – original draft. **Tariq Almomani:** Conceptualization, Investigation, Resources, Validation, Writing – original draft, Methodology, Resources, Formal analysis. **Stephen Snow:** Writing – original draft. **Rolf Witzmann:** Supervision, Funding acquisition. **Andreas Jossen:** Supervision, Funding acquisition. **Holger Hesse:** Conceptualization, Validation, Methodology, Resources, Formal analysis.

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5 Multi-use on large-scale battery storages

This chapter presents the paper titled *Unlocking the potential of battery storage with the dynamic stacking of multiple applications*. In the publication, a stationary energy storage system is modeled that serves several applications simultaneously. To effectively serve the applications, the EMS must be able to allocate the appropriate storage system capacities to the applications. Although such *multi-use* approaches have been presented in the literature, only the energy capacity has been allocated and other capacities, such as power, have been neglected [29, 123]. To close this research gap in the literature, the mixed-integer linear programming framework *mu_opt*[4] is developed, which can define an optimal allocation of storage capacities and thus execute an improved operation strategy.

For the study of *multi-use* operating strategies, four widely used energy storage applications are analyzed: Self-consumption increase, peak shaving, frequency regulation, and spot market trading. Since the study was conducted as part of a research project, a German battery storage system with 1.34 MWh energy content and 1.25 MW rated power is used for the simulations [178]. Calculations of battery cell degradation are based on existing models from literature [238]. As described in Section 2.2, applications are divided into BTM and FTM applications depending on their origin in the electricity value chain. With the separation of BTM and FTM applications, the presented approach allows the separation of energy and power into distinct partitions and any energy shift between these partitions is prevented to comply with unbundling laws. The objective function of the optimization framework maximizes the sum of the applications' profits over time. This allows the algorithm to decide opportunistically between the applications. Depending on the input data, the optimizer decides to which extent an application should be served or how much energy and power should be reserved/allocated to its partition. If, for example, a large load peak is detected by the algorithm, more energy and power is reserved for the PS application and the underlying BTM partition. At any time, it must be ensured that enough energy is reserved for the corresponding partition and application, and that energy conservation constraints are satisfied. Since the applications are also provided in defined markets with participation conditions, regulatory constraints, such as minimum provision time, must be met in addition to technical conditions.

Since the simultaneous provision of multiple applications also increases the probability of more energy throughput at the storage system, the issue of battery cell degradation is of particular importance in the context of *multi-use*. To avoid a high degree of degradation, opportunity costs for the energy throughput of the storage system are applied in the objective function. These opportunity costs are calculated from the expected EFC of the storage system and its investment costs. The study shows that the degradation-aware operation has a strong influence on the storage lifetime and thus on the profitability of the asset. A significant improvement in profitability is shown especially for *multi-use* strategies with the SMT application. By enabling opportunity costs for the energy throughput, the storage system's lifetime is increased from 2.5 to almost ten years, which significantly increases the expected profitability over its lifetime.

[4] Code is publicly available at the Gitlab repository: `https://gitlab.lrz.de/open-ees-ses/mu_opt`

As expected, when comparing the *multi-use* types, the dynamic *multi-use* proves to be the most lucrative approach from a techno-economic point of view [63]. Comparing sequential and parallel *multi-use*, the study shows that the exclusive operation of individual applications performs better than parallel *multi-use*. The reason for this effect is that the sequential *multi-use* still has the freedom to evaluate with each new optimization which application should be served next. In the parallel approach, on the other hand, a single global decision is made on how much energy and power to allocate to each application and partition. Due to the generally fluctuating input profiles (power, price, frequency, etc.), this results in better results for the most flexible solution, dynamic *multi-use* (cf. Sections 2.3.2 to 2.3.4). The boost in investment attractiveness due to *multi-use* demonstrated in this paper, makes a significant contribution to research, encouraging the accelerated deployment of battery energy storage.

Author contribution Stefan Englberger developed the idea of the study, developed the mixed-integer linear programming and model predictive control framework, carried out all simulations, and analyzed the data. Holger Hesse helped to parameterize the model and analyze the data. The manuscript was written by Stefan Englberger and was edited by Holger Hesse and Andreas Jossen. All authors discussed the data and commented on the results.

Unlocking the potential of battery storage with the dynamic stacking of multiple applications

Stefan Englberger, Andreas Jossen, Holger Hesse

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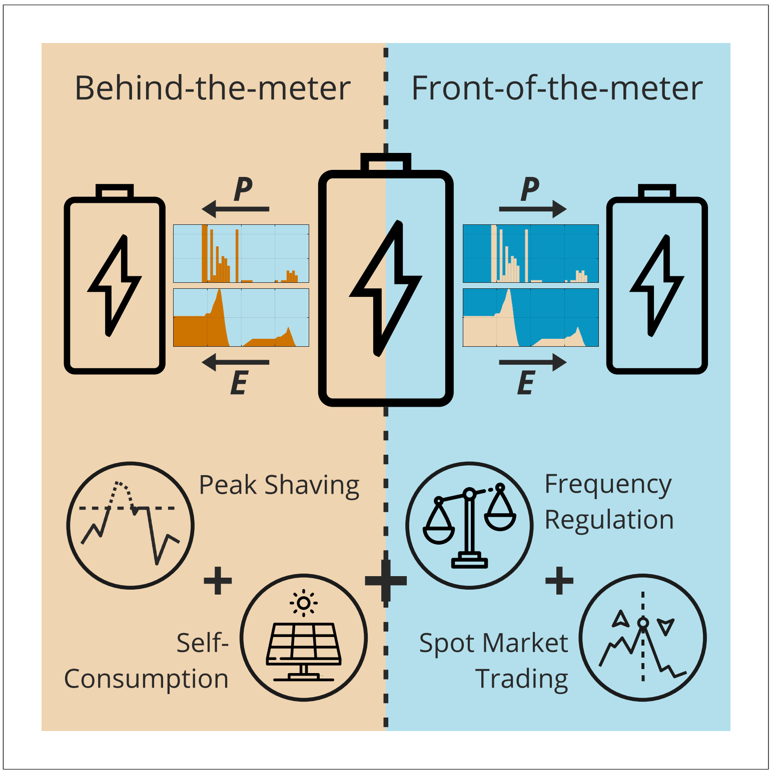
Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications



The simultaneous stacking of multiple applications on single storage is the key to profitable battery operation under current technical, regulatory, and economic conditions. Englberger et al. introduce an optimization framework for dynamic multi-use that considers both behind-the-meter and front-the-meter applications with distinct power and energy capacity allocations.

Stefan Englberger, Andreas Jossen, Holger Hesse

stefan.englberger@tum.de

HIGHLIGHTS

Stacking of multiple applications enables profitable battery operation

Dynamic stacking is superior to parallel or sequential multi-use

Optimized battery utilization yields significant techno-economic benefits

For realization of multi-use, both energy and power capacities need to be allocated

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Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications

Stefan Englberger,[1,2,*] Andreas Jossen,[1] and Holger Hesse[1]

SUMMARY

The ability of a battery energy storage system (BESS) to serve multiple applications makes it a promising technology to enable the sustainable energy transition. However, high investment costs are a considerable barrier to BESS deployment, and few profitable application scenarios exist at present. Here, we show that by tapping into multiple revenue streams using the dynamic stacking of applications, profitable operation is viable under current regulatory conditions. We develop a multi-use optimization framework which distinguishes between behind-the-meter and in-front-of-the-meter applications and considers how power capacity is allotted in addition to energy capacity allocation. The algorithm uses a rolling horizon optimization with an integrated degradation model and is fed with real-world data from a stationary lithium-ion battery in Germany. When combining peak shaving with frequency containment reserve, a net present value per Euro invested of 1.00 is achieved, and 1.24 with the addition of arbitrage trading on the intraday continuous market.

INTRODUCTION

With the undeniable need for a worldwide sustainable energy transition,[1,2] battery energy storage systems (BESSs) are a highly promising technology to successfully integrate large shares of renewable generation into existing energy systems.[3–6] Despite rapidly falling battery system costs,[7,8] the high investment requirement is primarily cited as the most significant barrier to energy storage deployment.[9–11] To help realize the high cost-reduction potential,[12] demand-pull policies can increase deployment and drive battery technologies down their respective learning curves.[8,10,13] As an alternative to the cost-side perspective, the investment attractiveness of energy storage can likewise be boosted by increasing revenue generation.

As a multi-purpose technology,[10] energy storage can serve a wide variety of applications.[14–16] For instance, a BESS can be an energy buffer for intermittent generation or increase grid power quality by providing frequency regulation services. Therefore, it can generate economic value for its stakeholders at different points in the electricity value chain.[10,17] However, under a single-use operation—in other words, serving one application only—BESSs struggle to attain profitability[18] and are often idle or underused.[17,19] Calendar degradation processes are still ongoing during battery idle times, where no application is actively served.[20,21] These can be reduced by serving multiple applications, as their complementing demands on the system result in better battery utilization. Thus, by stacking compatible applications on one BESS, a multi-use operation strategy can maximize storage value.[3,22,23]

[1]Institute for Electrical Energy Storage Technology, Technical University of Munich, Arcisstr. 21, 80333 Munich, Germany
[2]Lead Contact
*Correspondence: stefan.englberger@tum.de
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Central to the implementation of such a strategy is the question of how the limited energy and power capacities of the BESSs are allocated to the different applications. There are three types of multi-use, sequential, parallel, and dynamic, which differ in the way the applications are stacked.[24] The dynamic approach is the most flexible, as multiple applications can be served simultaneously with variable capacity allocations. In addition to the complex technical demands to the BESS's energy management system (EMS), regulatory requirements can pose another barrier to multi-use. For instance, unbundling laws require the separation of value generation in different stages of the electricity supply chain.[18] Behind-the-meter (BTM) applications serve end-consumer purposes, whereas applications improving grid stability are served in-front-of-the-meter (FTM).[17,24] To simultaneously address applications from different origins in the value chain, it is necessary that the physical storage system is separated into distinct virtual partitions.[25] Thus, for its practical implementation, a multi-use strategy requires an EMS and power electronics with the ability to clearly distinguish between BTM and FTM partitions, preventing any inter-energy exchange.

Several studies have investigated the various facets of multi-use, highlighting its high profitability potential.[18,19,26–30] Two gaps have been identified in the literature, one regulatory and the other technical, which need to be addressed to enable practical implementation. First, the distinct treatment of BTM and FTM, which will allow simultaneous service of both types of applications in compliance with regulatory requirements. Second, from a technical perspective, although both energy and power capacities are delivered by the BESS, these need to be allocated separately in a real-world system. We are not aware of a study that considers the role of power electronics in a multi-use operation; all of the identified quantitative studies address only the capacity allocation of energy, ignoring the equally important consideration of power. We developed a dynamic multi-use optimization framework to close the identified gaps and enable a practical implementation and profitable BESS operation under current regulatory conditions.

In this article, we analyze the techno-economic performance of single-use and multi-use operation strategies on a stationary lithium-ion BESS serving a characteristic commercial consumer in Germany. Our results show that the stationary BESS is highly profitable under a dynamic multi-use operation strategy. Based on our findings, stationary BESS stakeholders have a strong incentive to adopt this approach, and increased investor interest is expected. We focus on the implications to current and potential BESS stakeholders, but also discuss relevance to policy makers and identify areas for future research.

RESULTS

Increasing Performance through Application Stacking

We developed our multi-use optimization framework to evaluate the techno-economic performance of single-use and multi-use operation strategies on the same utility-scale, stationary BESS (see Experimental Procedures and Table S1 for details). To this end, the four applications—self-consumption increase (SCI; BTM), peak shaving (PS; BTM), frequency containment reserve (FCR; FTM), and spot market trading (SMT; FTM)—are compared and combined. We chose these applications because they enjoy the most widespread usage in stationary storage installations.[14] The BESS's equivalent full cycles (EFCs), state of health (SOH), and operating profit, by application and in total, at the end of the first year of operation, as well as the end-of-life (EOL) in years is determined for the seven scenarios (see Table 1). This is

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Table 1. Overview of the Techno-economic Performance of a Large-Scale BESS under Single-use and Multi-use Operations

	Annual Operating Profit/EUR kWh^{-1}					EFC	SOH/%	EOL/a
Scenario	PS	SCI	FCR	SMT	Total			
PS	43.3	−0.8	0	0	42.6	46.1	96.5	14.9
FCR	0	0	47.5	−1	46.5	128.6	96.5	14.7
SMT	0	0	0	58.8	58.8	214.7	95.1	9.5
PS + FCR	43.2	−0.7	45.4	−1.1	86.8	159.7	96	13.1
PS + SMT	42.9	−0.7	0	57.3	99.5	261	94.5	8.3
FCR + SMT	0	0	41.3	51.2	92.5	266.2	94.9	9.3
PS + FCR + SMT	42.9	−0.7	38.9	50.6	131.7	300.7	94.5	8.6

Behind-the-meter (BTM) applications peak shaving (PS) and self-consumption increase (SCI) relate to the power and energy costs, respectively, of the commercial consumer. Frequency containment reserve (FCR) and spot market trading (SMT) generate profit in-front-of-the-meter (FTM) on the frequency regulation and intraday continuous markets, respectively. The energy to power (E:P) ratio of the BESS is 1.34 MWh to 1.25 MW. The operating profit per installed energy capacity, number of equivalent full cycles (EFCs), and state of health (SOH) resulting from the first year of operation, as well as the end-of-life (EOL) is presented. BESS, battery energy storage system. /a, per annum.

followed by the illustration of the investment attractiveness by scenario (see Figure 1). Our results show that total profitability increases with the stacking of more applications, as do EFCs as the battery utilization also increases, but with only limited additional SOH loss.

Of the single-use scenarios, SMT generates the highest annual profit, but with significantly more EFCs and the shortest lifetime. The total profit in the PS scenario is composed of the revenue from the demand charge reduction (PS) and the cost of the energy purchased (SCI) to shave the demand peak. Analogously, in the single-use FCR scenario, total profit is made up of both the revenue generated on the frequency regulation market (FCR) and the net costs of scheduled transactions on the spot market (SMT). The single-use scenario with only SCI is not viable for the commercial player modeled in this work, as the residual load (load generation) is rarely negative and opportunities to generate revenue through energy savings do not arise. Comparing the PS and FCR single-use scenarios, identical SOHs and very similar battery lifetimes are observed despite the significant discrepancy in EFCs. This can be explained by the considerably greater depth-of-discharge required by PS, which makes a strong contribution to cyclic degradation.[21,31,32] Also, the BESS fluctuates around the medium state of charge (SOC) range during FCR provision; the SOC dependency of lithium-ion batteries is considered in the battery degradation model.[20,21]

The most profitable multi-use scenario is that with all three applications, PS + FCR + SMT. The authors agree that it is not viable to estimate multi-use earning potential simply by adding the respective earnings of the single-use scenarios,[30] due to trade-offs from power and energy capacity sharing between applications. Nevertheless, the extent of the synergistic effects is remarkably high in the multi-use scenarios modeled (for illustration, see Figure S1). For example, in the PS + FCR + SMT multi-use scenario, 99.2%, 83.6%, and 86.2% of the single-use earning potential is maintained, respectively. This positive effect is also demonstrated when two applications are combined, which indicates that under single-use operation the battery power and energy capacities are severely underused. Hence, the full earning potential of a BESS is realized only in a multi-use operation.

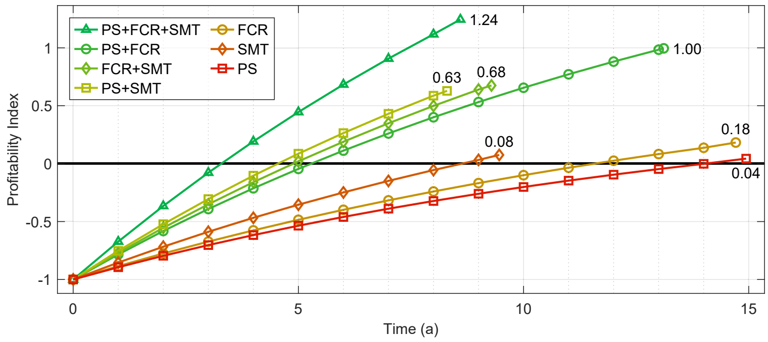

Figure 1. Investment Attractiveness of Single-use and Multi-use Scenarios

The profitability index equals the net present value normalized to the initial capital expenditures of 509 kEUR. Various combinations of the three applications, peak-shaving (PS), frequency containment reserve (FCR), and spot-market trading (SMT), are evaluated, considering the different battery energy storage system lifetimes applicable to the chosen operation strategy.

Each scenario is executed in the optimization model until the EOL is reached and the annual profits are discounted, to calculate the profitability index (PI) over battery lifetime, which equals the net present value (NPV) divided by the initial investment (for further details, see Experimental Procedures and Figure S2). The EOL criterion is set to 80% of remaining initial energy capacity, as the literature reveals that nonlinear degradation mechanisms and battery safety aspects are more prominent at lower SOH levels.[32,33] Investment costs of 380 EUR/kWh[34–36] for the given energy:power (E:P) ratio and a discount rate of 6%, as appropriate for utility-scale applications,[10] is assumed.

Figure 1 illustrates the PI development of the scenarios, with clear clusters emerging for single-use, multi-use with two, and multi-use with three applications. The most attractive single-use application is FCR, due to its high profitability and long lifetime. Nonetheless, the single-use applications are in a similar PI range of 0.04–0.18, with positive values reached only in the 9th (SMT), 12th (FCR), and 14th years (PS) following the initial investment. Considering the uncertainty of revenue earning potential in the future of each application, establishing multi-use capability should be a high priority for any stationary BESS stakeholders operating in single use.

The positive contribution of application stacking is clearly illustrated by the significantly higher PI range of 0.63–1.24, with positive values attained significantly sooner (during 4th and 5th/6th year of operation with three and two applications, respectively). In any scenario with SMT, an accelerated battery degradation is observed, due to the application's increased energy throughput. By considering the cycles' opportunity costs in the model, only the most profitable trades are scheduled and cyclic degradation is reduced (see Experimental Procedures). The two most attractive application combinations, PS + FCR + SMT and PS + FCR, both require the clear distinction between BTM and FTM to satisfy the regulatory requirements.[17,24,25] When comparing these scenarios, the assumed discount rate plays a significant role, due to the longer lifetime of the latter scenario. For instance, without discounting annual profits, the scenarios' PI would equal 1.94 and 1.93, respectively. The convex shape of the PIs over time is explained by the decreasing usable energy capacity and the greater discounting effect further into the future. The results make a strong case for the dynamic stacking of multiple stationary applications on a single utility-scale BESS, because synergies between applications lead to better utilization

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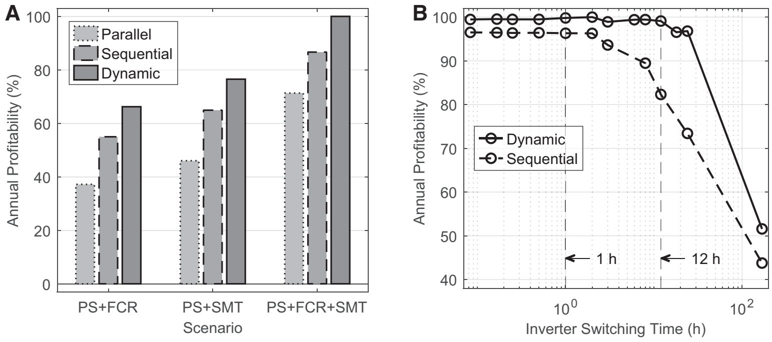

Figure 2. Profitability Comparison of Parallel, Sequential, and Dynamic Multi-use Approaches

(A) Comparison of parallel, sequential, and dynamic multi-use for the applications peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT) as well as an inverter switching time of 12 h. Parallel multi-use is characterized by a constant allocation of storage capacity, whereas the sequential operations serve the behind-the-meter (BTM) or front-of-the-meter (FTM) partition exclusively. The dynamic multi-use approach yields the highest profit, as it combines the advantages of its two predecessors.

(B) Annual profitability for the dynamic and sequential multi-use approaches over inverter switching time. Inverter switching time determines the frequency with which battery energy storage system capacities can be reallocated. The relative profitability is illustrated for the PS + FCR + SMT scenario, with inverter switching times from 5 min to 7 days.

without a noteworthy lifetime contraction. By spreading dependence from a single revenue stream to multiple sources, multi-use also diversifies risks due to uncertain future price developments of the respective applications. This is an important factor for current and potential BESS stakeholders to consider.

Economic Impact of Different Multi-use Approaches

The matter of how limited battery energy and power capacities are allocated is an important consideration when implementing a multi-use strategy (see Experimental Procedures and Figure S3 for further details on the three multi-use approaches). The inverter switching time is defined as the frequency with which the power reallocation can take place. Although this article focuses on the merits of a multi-use approach using dynamic capacity allocations, the economic impact of the alternative, sequential and parallel, approaches is also presented (see Figure 2A). Dynamic multi-use demonstrates superior profitability. The parallel strategy is the least preferable economically, despite the fixed allocations between BTM and FTM being optimized beforehand in our implementation. The higher profitability of the sequential strategy reveals that the subsequent switching between applications is more effective than the parallel sharing of capacities. Dynamic multi-use has the advantage of simultaneously serving both BTM and FTM applications, in contrast to the sequential strategy. This ability makes the profitability of the dynamic strategy more stable against longer inverter switching times (see Figure 2B). Thus, if it is not possible to implement a dynamic multi-use approach, then we recommend the sequential strategy over the parallel allocation of BESS capacities.

Dynamic Multi-use Optimization Framework

The developed multi-use optimization framework can be integrated into a state-of-the-art EMS, enabling a dynamic multi-use operation strategy on a real-world system, while upholding detailed technical and regulatory requirements. For an illustration of how this real-world implementation is executed, including feedback loops between the EMS and the physical BESS, see Figure S4.

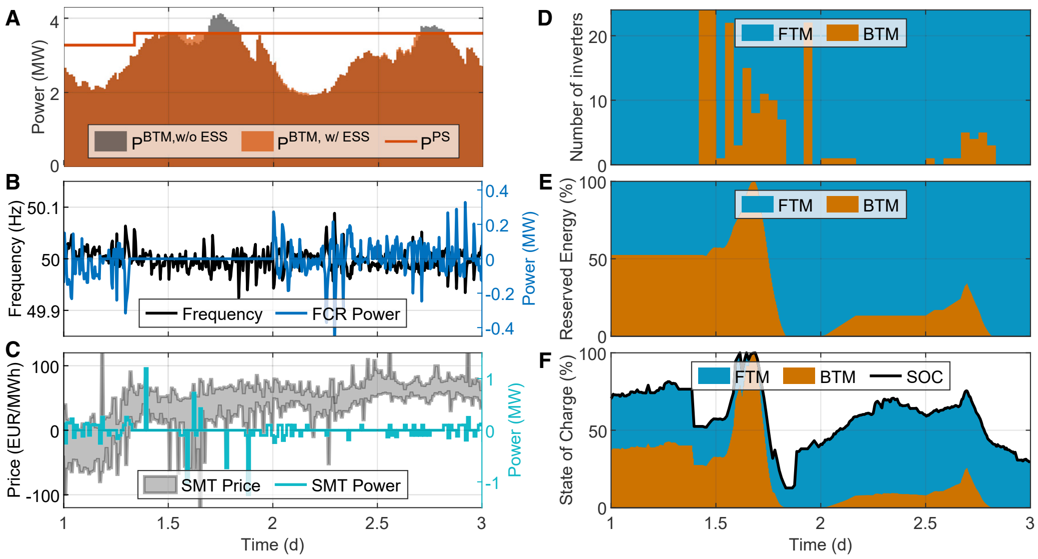

Figure 3. Optimization Framework Outputs of a Dynamic Multi-use Operation Strategy with Peak Shaving (PS), Frequency Containment Reserve (FCR), and Spot Market Trading (SMT)

A 2-day excerpt is shown for (A) the residual load on the behind-the-meter (BTM) partition and the respective PS threshold; (B) grid frequency input profile and the FCR power provided by the battery energy storage system (BESS); (C) price corridor on the intraday continuous market and the power traded by the BESS; (D) BTM and front-of-the-meter (FTM) power allocation; (E) BTM and FTM energy content allocation; and (F) state of charge (SOC) of the BESS and the respective energy allocation.

This framework makes several unique contributions, including the unprecedented consideration of power capacity as well as energy allocation and the technical implementation of distinct BTM and FTM partitions, which allows both application types to be served simultaneously. Central to this detailed technical consideration is the BESS topology (see Figure S5), which enables implementation in compliance with technical and regulatory conditions (e.g., through its distinction between BTM and FTM). Although the optimization is deterministic, a rolling horizon is implemented with successive input information updates, which increases the robustness of the results against forecast uncertainties (see Figure S6 for illustration). Furthermore, the model is degradation aware, meaning that the opportunity costs due to battery degradation losses are considered in decision making about the optimization tool (see Experimental Procedures and Figure S7).

Figure 3 demonstrates the behavior of the three applications (Figures 3A–3C) and the power and energy allocation (Figures 3D–3F) under the implemented dynamic multi-use operation strategy. In this article, the model parameters are based on a real-world stationary BESS located in Germany. Due to data availability, the model assumptions are designed around German regulatory and technical constraints. The depicted scenario shows characteristic results (see Table S1 for input profile and parameter assumptions), which we validated by conducting over 400 scenarios with varying sensitivities (see Figures S8–S12). Results of the sensitivity analyses show that profit variation subject to different input profiles is significantly more robust in a multi-use scenario (see Figures S9 and S11). Figure 3A demonstrates how the PS threshold, above which residual load is compensated for by the BESS, is adjusted upward, depending on the height and area of the foreseen peaks and the available capacities of BESS. This occurs repeatedly during the simulation period as new information becomes available, until the optimal PS threshold is determined (see Experimental Procedures). No FCR is provided by the

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BESS (Figure 3B) while the peak is being shaved, because most of the energy content is reserved for the BTM partition (Figure 3E). Figure 3D and 3E demonstrate how the allocation of power and energy capacities differ notably in a dynamic multi-use implementation. Using a parallel multi-use approach, these reserved power and energy capacities would be constant over time. Whereas Figure 3E shows the partitioning of energy by BTM and FTM relative to the total reserved energy content, Figure 3F depicts the reserved energy content relative to total energy content, or the SOC of BESS.

The implemented model ensures that power and energy capacity allocation is optimal, depending on the input profiles, to maximize applications' operating profits in a degradation-aware manner while upholding necessary constraints (see Experimental Procedures).

DISCUSSION

Our results show that a dynamic multi-use operation strategy yields substantially higher profitability than any single-use operation. The application combinations of PS + FCR and PS + FCR + SMT generate especially attractive results for investors, with swift payback periods and high positive NPVs. Based on these findings, stationary BESS stakeholders have a strong incentive to adopt a dynamic multi-use approach. Based on our findings, the main barrier to BESS deployment—its lack of attractiveness to investors due to high initial investment costs—can be removed by maximizing its earning potential through application stacking. Policy makers interested in accelerating energy storage deployment to facilitate a sustainable energy system transformation should note that multi-use operation has the potential to substitute the need for costly deployment subsidies.[18] The dynamic multi-use framework presented here is being implemented on a real-world stationary BESS. The authors are highly confident that once evidence from successful multi-use operations is available, private sector investment in this area will be expedited further. We recommend that policy makers draft policy to facilitate the proliferation of multi-use operation strategies. In addition, an effort should be made to remove remaining regulatory barriers to the deployment of energy storage at large, such as a lack of a clearly defined role for energy storage in the electricity grid and market designs that are not technology neutral.[9,18,37,38]

The presented model makes a unique contribution to the literature, especially in its focus on the detailed technical capabilities required for a real-world dynamic multi-use operation, such as the BTM and FTM distinction and separate power and energy capacity allocation. Nevertheless, several assumptions are made, which need to be discussed to accurately interpret the presented results and to identify areas for further research. First, it is assumed that all bids on the frequency regulation and intraday continuous market are completed. Second, input data from 2019 are used for the full lifetime of the modeled BESS, which disregards the significant uncertainty regarding future load profile and market developments. For the SMT application's profit, the average value of the best- and worst-case scenarios is calculated as a realistic midpoint, using the high-low and weighted average price profiles, respectively. In addition, since the greater deployment and participation of stationary and mobile BESSs in the FCR and spot markets can lead to market saturation,[26] ensuing revenue generation is likely to decrease due to falling prices and smaller price spreads, respectively. Strongly falling FCR market prices in recent years,[24,39] which severely reduced the revenue potential of this use case, demonstrates the danger of depending on a single revenue stream. By acquiring multi-use capability, dependence on a single revenue stream is avoided and the risk of future earning uncertainty is diversified over multiple revenue sources. Thus, regardless of future market developments, a stationary BESS technically capable of addressing multiple applications, in various points in the electricity value chain, is better placed to make use of newly arising opportunities than one locked into a single-use case.

In our implementation, the E:P ratio and sizing of the BESS are based on data from a real-world lithium-ion battery in Germany. From this starting point, the optimal power and energy allocation under various single- and multi-use scenarios is determined and analyzed. In future research, the sizing and E:P dimensioning for the stationary storage could be optimized depending on given application combinations. In addition, the developed framework can be extended to include new applications to explore further combinations,[40] as well as the implementation of a more detailed efficiency model on the inverter level. Also, adjusting the model's input parameters and profiles to reflect the different conditions in other countries would illustrate to which extent results differ across nations.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

Further information and requests for resources and materials should be directed to and will be fulfilled by the Lead Contact, Stefan Englberger (stefan.englberger@tum.de).

Materials Availability

This study did not generate new unique materials.

Data and Code Availability

The datasets generated in this study are available from the Lead Contact on request.

Performance Indicators

In this work, four primary performance indicators are used to analyze the techno-economic effectiveness of multi-use operation strategies: operating profit, EFCs, SOH, and PI. Total operating profit is the sum of each application's profit (Equation 1). The profit from the PS application, $\mathbb{P}^{PS}$ (Equation 2), originates from the reduced costs for power-related surcharges. Thus, it equals the difference between power costs with ($\mathbb{C}^{PS,w/BESS}$) and without ($\mathbb{C}^{PS,w/oBESS}$) a BESS used for PS. Likewise, the profit from SCI, $\mathbb{P}_t^{SCI}$, represents the cost savings for energy-related charges to the end consumer with a BESS increasing self-consumption (Equation 3). Operating profit from FCR, $\mathbb{P}^{FCR}$, represents the revenue earned on the frequency regulation market. SMT profit, $\mathbb{P}^{SMT}$, is generated using price spreads at the intraday continuous market, whereby energy is sold at high prices and purchased when the price is low.

$$\mathbb{P}^{Total} = \mathbb{P}^{PS} + \mathbb{P}^{SCI} + \mathbb{P}^{FCR} + \mathbb{P}^{SMT} \quad \text{(Equation 1)}$$

$$\mathbb{P}^{PS} = \mathbb{C}^{PS,w/oBESS} - \mathbb{C}^{PS,w/BESS} \quad \text{(Equation 2)}$$

$$\mathbb{P}_t^{SCI} = \mathbb{C}_t^{SCI,w/oBESS} - \mathbb{C}_t^{SCI,w/BESS} \quad \text{(Equation 3)}$$

The SOH of the BESS is the quotient of the remaining energy capacity, $E_t^{remaining}$, and the nominal energy content (Equation 4). For each 5-min time step, t, the remaining energy capacity results from the integrated degradation model, originally published by Schmalstieg et al.[21] It differentiates between cyclic and calendar degradation while considering parameters such as depth-of-discharge, cumulative charge throughput, temperature, and voltage level. The EFC of the BESS is calculated by halving the absolute change in SOC from $t-1$ to t (Equation 5). In turn, the SOC

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is defined in Equation 6 as the actual energy content of the BESS, E_t^{actual}, divided by its remaining energy capacity.

$$\mathrm{SOH}_t = \frac{E_t^{remaining}}{E^{nominal}} \quad \text{(Equation 4)}$$

$$\mathrm{EFC}_t = \frac{\left|E_t^{actual} - E_{t-1}^{actual}\right|}{2 \times E^{nominal}} \quad \text{(Equation 5)}$$

$$\mathrm{SOC}_t = \frac{E_t^{actual}}{E_t^{remaining}} \quad \text{(Equation 6)}$$

Investment attractiveness is evaluated using the PI (Equation 7), which equals the NPV of the operation strategy, normalized over the capital expenditures of the BESS, $\mathbb{C}^{invest}$. According to Equation 8, the NPV is defined as the discounted operating profits, $\mathbb{P}_n^{Total}$, until the EOL of the BESS is reached, minus the initial investment.

$$\mathrm{PI} = \frac{\mathrm{NPV}}{\mathbb{C}^{invest}} \quad \text{(Equation 7)}$$

$$\mathrm{NPV} = -\mathbb{C}^{invest} + \sum_{n=1}^{EOL} \frac{\mathbb{P}_n^{Total}}{(1+i)^n} \quad \text{(Equation 8)}$$

Multi-use Approaches and Their Implementations

The three types of multi-use presented in this article differ in their approach to how the energy and power capacities of the BESS are allocated to the multiple applications (see Figure S3 for illustration). Parallel multi-use applies a fixed allocation, whereas the sequential approach serves one application exclusively, switching between applications over time. Dynamic multi-use combines the benefits of both.

In this work's implementation, the allocation occurs not on an application basis but on the distinction between BTM and FTM partitions. This means that the limitations of the parallel and sequential approaches do not apply to multiple applications within the same partition. Thus, in the sequential strategy with PS + FCR + SMT, the two FTM applications are combined dynamically. In the model, the default inverter switching time is 1 h. To guarantee comparability between the strategies, the optimal allocation values, on average, of the dynamic multi-use strategy are used as the input for the fixed fractional partitioning of the parallel strategy.

Dynamic Multi-use Optimization Formulation

To model the real-world problem, a mixed-integer linear programming framework is established in MATLAB. To reduce the computation time for each optimization, we use the Gurobi solver.[41] The optimization objective, given in Equation 9, maximizes the operating profit from FCR provision and SMT, $\mathbb{P}_t^{FCR}$ and $\mathbb{P}_t^{SMT}$, and minimizes the energy and power costs for the end consumer, $\mathbb{C}_t^{BTM,E}$ and $\mathbb{C}_t^{BTM,P}$. The opportunity costs of battery cycles, $\mathbb{C}^{cycle}$, are also minimized and calculated using Equation 10, whereby the capital expenditures of the BESS are divided by a conservative estimate of total EFCs over the lifetime of a BESS, $\mathrm{EFC}^{expected}$. The resulting estimated capital expenditures per cycle are multiplied by the cycles per time step. This ensures that only activities that generate higher profitability than the cycle opportunity costs are executed. By limiting less profitable cycles, degradation is reduced and degradation awareness is thereby introduced to the model.

$$\max z\,, z = \sum_{t=1}^{N} \left(\mathbb{P}_t^{FCR} + \mathbb{P}_t^{SMT} - \mathbb{C}_t^{BTM,E}\right) - \mathbb{C}^{BTM,P} - \mathbb{C}^{cycle} \quad \text{(Equation 9)}$$

$$\mathbb{C}^{cycle} = \sum_{t=1}^{N} \left(EFC_t \times \frac{\mathbb{C}^{invest}}{EFC^{expected}} \right) \quad \text{(Equation 10)}$$

In the following, the model constraints of the optimization problem are introduced, first for the implementation of the power and energy partitioning of the storage and then the respective storage applications examined in this work: PS, SCI, FCR, and SMT.

Energy and Power Allocation

The battery topology, which includes the cells, inverters, busbar, electricity meters, EMS, thermal management system, and battery management system, is central to enabling the power and energy allocation implemented in this article (see Figure S5 for the detailed topology). To enable the distinction between BTM and FTM, the physical storage system is divided into two BTM and FTM partitions.[25] It is essential that the energy flow between the BTM and FTM partitions is prohibited, for regulatory reasons (i.e., unbundling laws that denote the separation of different parts of the electricity value chain).[18]

In the following, the constraints governing the energy and power characteristics of the storage are outlined. To calculate the actual energy content of the two storage partitions and to operate the BESS within a technically feasible area, Equations 11 and 12 are introduced. These consider the actual energy content of the respective storage partition at the previous point in time, E_{t-1}^{act}, the energy charged, E_t^{CH}, and energy discharged, E_t^{DCH} during the time step t. The in-going and out-going energy flows are calculated considering the efficiency values of the system components during charging, η^{CH}, and discharging, η^{DCH}. The usable energy content, E_t^{use}, of the storage partitions can be understood as reserved energy per partition, and the self-discharge, E_t^{SD}, is weighted proportionally for each partition, based on the reserved energy content.

$$E_t^{act,BTM} = E_{t-1}^{act,BTM} + E_t^{CH,BTM} \times \eta^{CH} - E_t^{DCH,BTM} \times \frac{1}{\eta^{DCH}} - E_t^{SD} \times \frac{E_t^{use,BTM}}{E_t^{use}} \quad \text{(Equation 11)}$$

$$E_t^{act,FTM} = E_{t-1}^{act,FTM} + E_t^{CH,FTM} \times \eta^{CH} - E_t^{DCH,FTM} \times \frac{1}{\eta^{DCH}} - E_t^{SD} \times \frac{E_t^{use,FTM}}{E_t^{use}} \quad \text{(Equation 12)}$$

Due to battery cell degradation, the usable energy content on the system level declines over time. Equation 13 ensures that the BTM and FTM partitioning is upheld for the usable energy content. The actual energy content is required to calculate ongoing processes on the physical BESS level, such as the calendar and cycle degradation losses. Since the actual energy content per partition may move within the reserved or usable energy range, this is considered in the mathematical formulation using the inequalities in Equations 14 and 15, where $E_t^{act,BTM}$ and $E_t^{act,FTM}$ are defined as the respective actual energy contents of the storage partitions.

$$E_t^{use} = E_t^{use,BTM} + E_t^{use,FTM} \quad \text{(Equation 13)}$$

$$E_t^{act,BTM} \leq E_t^{use,BTM} \quad \text{(Equation 14)}$$

$$E_t^{act,FTM} \leq E_t^{use,FTM} \quad \text{(Equation 15)}$$

In addition to the energy-related component of the storage system, the power electronics is the decisive factor for the system's power and consist of several inverters. Equation 16 ensures that all of the inverters of the BESS x_t are allocated to either the BTM or FTM partition, where x_t^{BTM} and x_t^{FTM} represent the integer number of

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allocated inverters for the two partitions. Hence, unlike the allocation of energy capacity, which is continuous, the power capacity allocation is discrete (see Figures 3D and 3E).

$$x_t = x_t^{BTM} + x_t^{FTM} \quad \text{(Equation 16)}$$

Peak Shaving

The inclusion of power-related costs in electricity billing creates an incentive to reduce peak power demand.[10] Although the electricity tariff structures differ by country, power-related costs are generally implemented at least for a portion of electricity consumers, with the highest peak power within a billing period, typically of 1 year, being multiplied by the power surcharge. In Germany, electricity consumers with an annual consumption >100 MWh are required to pay a power surcharge in addition to the grid tariff for consumed energy.[42] The power price and grid tariff (energy charge) depends on the consumer's residual load profile.[42] For a detailed listing of assumed parameters, see Table S1. The network charges, which consider the costs for upstream grid levels, grid infrastructure, provision of system services, and the coverage of transmission losses, are reflected in the energy and power surcharges.

The PS application is particularly interesting with regard to stationary energy storage,[43] because with this flexibility, high power peaks can be covered by the BESS, which is recharged at times of low load. Value is created by decreasing the maximum power peak in the billing period, $\widehat{P}^{BTM}$, which when multiplied by the power surcharge, $p^{BTM,P}$, results in lower power-related expenses, $\mathbb{C}^{BTM,P}$ (Equation 17):

$$\mathbb{C}^{BTM,P} = p^{BTM,P} \times \widehat{P}^{BTM} \quad \text{(Equation 17)}$$

The prediction quality of the power peaks is significant. Here, not only the height of the peak but also its energy content is relevant, since the integral of the power needs to be covered by the BESS. Thus, considering the residual load, it is essential to define an effective PS threshold above which the power is provided by the storage system. In the multi-use operation of a BESS, an appropriate PS threshold is even more vital. If the peak shaving limit is too low, a high amount of energy and power is reserved for the PS application, which can limit or prevent the service of other applications.

The residual load profile used is selected from a sample set of commercial and industrial profiles, resulting in some sample bias (see the input profile information in the Supplemental Experimental Procedures and Figures S10 and S11 for the effect on the profitability of different residual load profiles).

Self-Consumption Increase

In general, decentralized renewable generation is incentivized using feed-in tariffs or other demand-pull policies,[10] whereby the producer receives a remuneration price for energy injected into the grid. Typically, the purchase price, or grid tariff, is higher than the remuneration offered, leading to an incentive to maximize self-consumption.[28,29] If the generated power exceeds the load, then a BESS can be used to reduce the supply demand gap. In Germany, where the incentive to self-consume is very pronounced for households, the SCI application is cost-effective.[44] The baseline sample set shows only rare occasions of negative residual load, meaning that the generated power is generally lower than the demand. Thus, there is little to no excess power for the energy storage to buffer, resulting in limited added value from this application. Under different scenario conditions (i.e., with greater dimensioning of the renewable generator), this application would be more appropriate.

For a prosumer of renewable generation, net electricity costs (energy charge), $\mathbb{C}_t^{\mathrm{BTM},E}$, in a self-consumption scenario are calculated by subtracting the electricity revenues from the electricity purchase expenses (Equation 18), whereby $E_t^{\mathrm{BTM,sell}}$, $E_t^{\mathrm{BTM,purch}}$, $\mathrm{p}^{\mathrm{BTM,E,purch}}$, and $\mathrm{p}^{\mathrm{BTM,E,sell}}$, are the energy sold, purchased, grid tariff, and feed-in tariff remuneration, respectively. See Table S1 for assumed values.

$$\mathbb{C}_t^{\mathrm{BTM},E} = E_t^{\mathrm{BTM,purch}} \times \mathrm{p}^{\mathrm{BTM,E,purch}} - E_t^{\mathrm{BTM,sell}} \times \mathrm{p}^{\mathrm{BTM,E,sell}} \quad \text{(Equation 18)}$$

Frequency Containment Reserve

Within the ENTSO-E transmission grid, three products for electricity balancing exist: FCR, frequency restoration reserve, and replacement reserve.[45] These three products of the load-frequency-control structure in turn contain several processes. The primary control reserve, which is assigned to the FCR product, is the most economically interesting process for BESSs in central Europe, and therefore also in Germany. Within the FCR provision, the Austrian, Belgian, Dutch, French, German, and Swiss transmission system operators purchase the FCR service in a common market. The provided FCR must be offered in 1-MW increments. From July 2020, the duration of product delivery was reduced from daily to 4-h blocks.[45] The greater flexibility of the 4-h provision blocks is implemented in this model.

For the stable provision of FCR, a BESS must be designed to provide the allocated FCR power at any time for an extra 15 min.[46] Also, the BESS should guarantee 25% additional reserve power to cover scheduled transactions on a spot market, keeping the SOC in the permitted range during a full unilateral FCR call.[46] Hence, for the provision of 1 MW FCR power, the rated power of the storage system must be at least 1.25 MW, whereby the 0.25 MW reserve is also available for the SMT application. The usage of this reserve power by BTM applications is not permitted since the constraint for FCR reserve power would be violated.

During an active FCR period, the EMS of the BESS must react without delay to any frequency fluctuation. This means that the FCR active power is a function of the grid frequency with certain degrees of freedom. One of these degrees of freedom is the overfulfillment of FCR power, by up to 20%. Within the frequency dead band of ± 10 mHz from the nominal grid frequency of 50 Hz, the technical rules for providing FCR are less strict.[46]

Value is generated from FCR provision through the price awarded per MW, $\mathrm{p}_t^{\mathrm{FCR}}$, multiplied by the total FCR power, $P_t^{\mathrm{FCR,alloc}}$ (Equation 19). However, a portion of this generated value can be shared with an aggregator.

$$\mathbb{P}_t^{\mathrm{FCR}} = P_t^{\mathrm{FCR,alloc}} \times \mathrm{p}_t^{\mathrm{FCR}} \quad \text{(Equation 19)}$$

In our model, an aggregator provides flexibility in the FCR application, allowing the battery operator to participate in the market with smaller power portions than the 1 MW requirement. For this service, the aggregator is allocated a portion of the remunerated power, which is linearly dependent on the bid size. The smaller the bid size, the greater the risk and portion of remunerated power received by the aggregator. Equation 20 shows the linear relationship between the power remunerated for the FCR provision, $P_t^{\mathrm{FCR,rem}}$, and the bid power, where k is the slope and d the y-intercept (see Equations S1 and S2 for the mathematical definition of k and d). With an increasing k, the incentive for the battery operator to participate in the FCR market

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with high power bids also increases, so as to minimize the relative surcharge paid to the aggregator. (See Table S1 for the assumed values applied to the FCR application.) It turns out that with the resulting incentive to bid with 1 MW when possible, the aggregator is not strictly necessary, and the FCR profitability potential would be higher without an aggregator. Still, we chose this implementation as it is more realistic for small players who are otherwise unable to participate in the FCR market and are thus willing to pay for the provided flexibility.

$$P_t^{FCR,rem} = \begin{cases} P_t^{FCR,alloc} \times k + d, & P^{FCR,min} \leq P_t^{FCR,alloc} \leq P^{FCR,max} \\ 0, & \text{otherwise} \end{cases} \quad \text{(Equation 20)}$$

Spot Market Trading

Another FTM application for BESSs is energy trading on spot markets. In Germany, the three markets day-ahead auction, intraday auction, and intraday continuous market are of interest for the participation of BESSs.[47] Since BESSs have particularly short response times and are generally designed for a short temporary storage of energy, it is economically advantageous to have high price differences within short time spans.[26] With high price spreads, the economic result of arbitrage trading improves.

Three price signals from the intraday continuous market are used: weighted average price, low price, and high price. The first demonstrates only meager price variations, whereas the latter two represent the maximum variation possible. Thus, profits are calculated for both the weighted average and high–low price signals, representing the worst- and best-case results, and then their average is presented as a realistic midpoint (see Figure S12). Depending on several factors, including the sophistication of the intraday continuous price forecast and response time of communication equipment, the real-world implementation of the SMT application will generate higher or lower profits than the assumed midpoint.

To ensure that power is not purchased and sold during the same time step, Equation 21 is introduced, where $a_t^{FTM,purch}$ and $a_t^{FTM,sell}$ are binary variables.

$$a_t^{FTM,purch} + a_t^{FTM,sell} \leq 1 \quad \text{(Equation 21)}$$

According to existing market regulations, the purchased and sold power, $P_t^{FTM,purch}$ and $P_t^{FTM,sell}$, must meet the minimum order requirement, $P^{SMT,MIN}$, of 100 kW[47] (Equations 22 and 23). The minimum offer duration period of 15 min is also maintained in our model.

$$a_t^{FTM,purch} \times P^{SMT,MIN} \leq P_t^{FTM,purch} \quad \text{(Equation 22)}$$

$$a_t^{FTM,sell} \times P^{SMT,MIN} \leq P_t^{FTM,sell} \quad \text{(Equation 23)}$$

Thus, value generation through the SMT application, $\mathbb{P}_t^{SMT}$, occurs with the realization of arbitrage opportunities (Equation 24), where high selling prices, $p_t^{SMT,sell}$, and low purchase prices, $p_t^{SMT,purch}$, are used to generate profit.

$$\mathbb{P}_t^{SMT} = \Delta t \left(P_t^{FTM,sell} \times p_t^{SMT,sell} - P_t^{FTM,purch} \times p_t^{SMT,purch} \right) \quad \text{(Equation 24)}$$

In our model, for each transaction on the spot market, the physical delivery is also executed.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.xcrp.2020.100238.

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AUTHOR CONTRIBUTIONS

S.E., A.J., and H.H. designed the study. S.E. developed the model and optimization algorithm. S.E. and H.H. carried out the data search. S.E. and H.H. carried out the analyses. S.E., A.J., and H.H. wrote the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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Cell Reports Physical Science, Volume *1*

Supplemental Information

Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications

Stefan Englberger, Andreas Jossen, and Holger Hesse

Supplemental Experimental Procedures

Input Profiles

For the residual load 37 real-world profiles from industrial and commercial customers in Germany are utilized.[1] To analyze the effect of the grid frequency on frequency containment reserve (FCR) application in single and multi-use, frequency data from 2014 to 2019 is used.[2] The compensation of the FCR is considered with the data price signal from 2019 in Germany.[3] As the product duration for FCR has changed in July 2019 to daily auctions,[4] the daily price scheme is also applied for the first half of 2019. In order to comply with regulations beginning with July 2020, the daily signal with a 4 hour resolution is applied in this work.[4] The three spot market trading (SMT) price signals (weighted average, high, and low) are from the German intraday continuous market from 2019.[5]

Table S1: Model parameters for optimization, energy storage, and applications.

Parameter	Value	Unit	Parameter	Value	Unit
Optimization parameters			**Peak shaving (PS)**[6]		
Sample time	5	minutes	Power surcharge	100	EUR/kW
Optimization horizon	24	h	Billing period	1	a
Rolling period	8	h	**Self-consumption increase (SCI)**[7]		
Storage system			Grid tariff	0.1405	EUR/kWh
System energy content	1,340	kWh	Remuneration price	0.1061	EUR/kWh
System power	1,250	kW	**Frequency containment reserve (FCR)**[4]		
Inverter amount	24	-	Provision period	4	h
Initial SOH	100	%	Minimum power	100	kW
SOC limits	[0, 100]	%	Maximum power	1,000	kW
Battery efficiency	97	%[8]	Minimum remuneration	60	%
Inverter efficiency	96	%[9]	Maximum remuneration	85	%
Maximum charge rate	1	C[10]	Nominal grid frequency	50	Hz
Maximum discharge rate	1	C[10]	Frequency droop	0.4	%
Cell chemistry	NiMnCo	(NMC)[11]	Frequency dead band	10	mHz
Self-discharge	1.5	%/month[8]	Overfulfillment	120	%
Ambient temperature	20	°C[11]	**Stock market trading (SMT)**[5]		
Nominal cell capacity	2.05	Ah[11]	Trading period	15	minutes
EFC capability	3,000	EFC[11]	Minimum power	100	kW
Annual consumption	20	GWh	Trading fee	0.1425	EUR/MWh

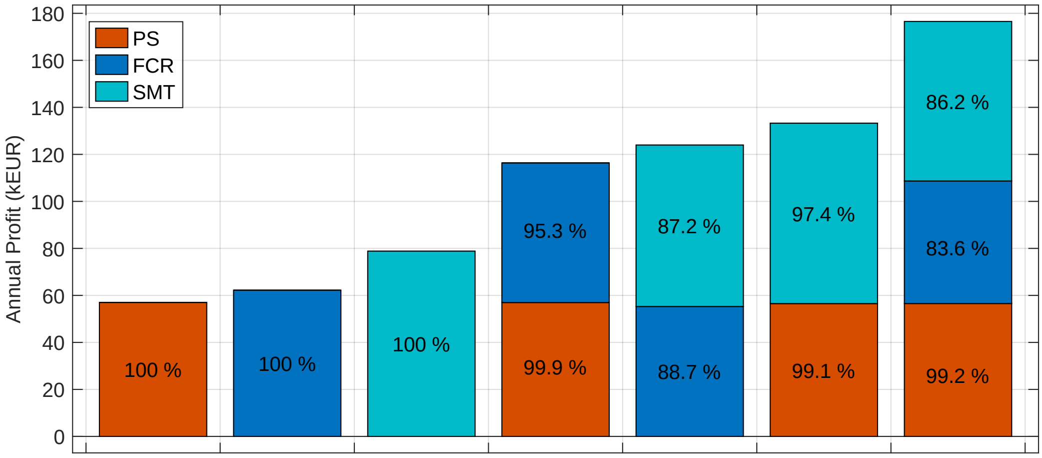

Figure S1: Illustration of remaining profitability per application, relative to single-use operation, after combining multiple applications on the same battery energy storage system. High synergistic effects are illustrated, between 83.6 % and 99.9 % of original earning potential maintained with multi-use operation. The shown applications are peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT).

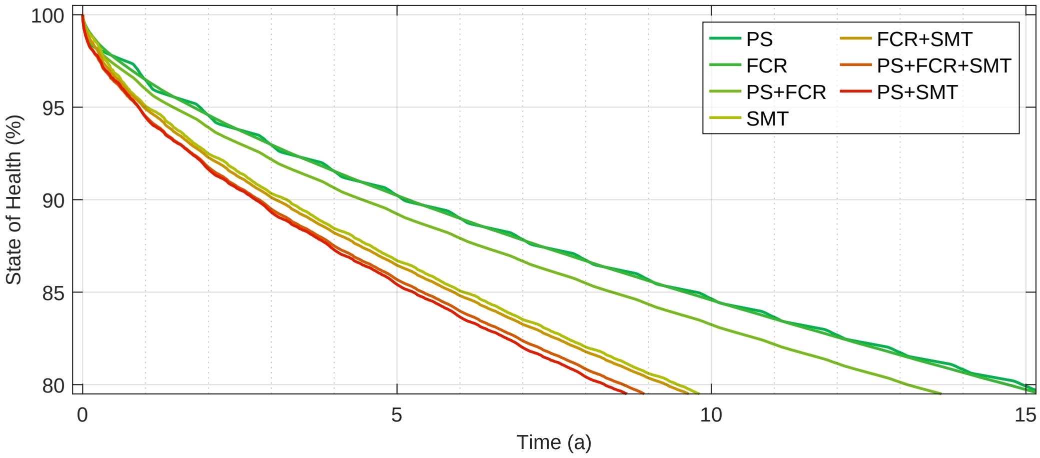

Figure S2: State of health (SOH) development over time. Seven single and multi-use scenarios are shown for the duration until the end-of-life of the BESS is reached. The shown applications are peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT).

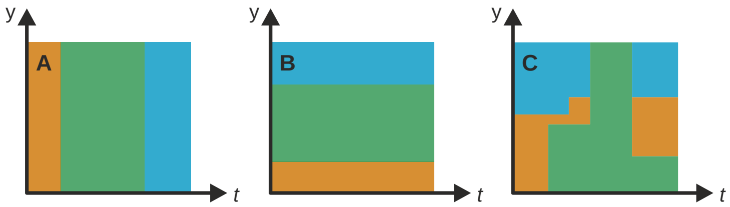

Figure S3: Overview of the three methodologies of stacking applications in multi-use: sequential, parallel, and dynamic (adapted from[12]). The y-axis depicts the degree of allocation, which can be either a portion of the battery's power or energy capacity. The latter is limited by the system's capacity (Ah), whereas the former is limited by both the minimum value of the battery cell's C-Rate and the system's power electronics. Sequential multi-use (A) exhibits the exclusive service of one application at a time whereas all applications are served simultaneously in parallel multi-use (B). Dynamic multi-use (C) is a hybrid of sequential and parallel multi-use. Unlike parallel multi-use, where the degree of allocation per application remains fixed over time, dynamic multi-use adjusts the portioning of the storage's power and energy capacities dynamically over time.

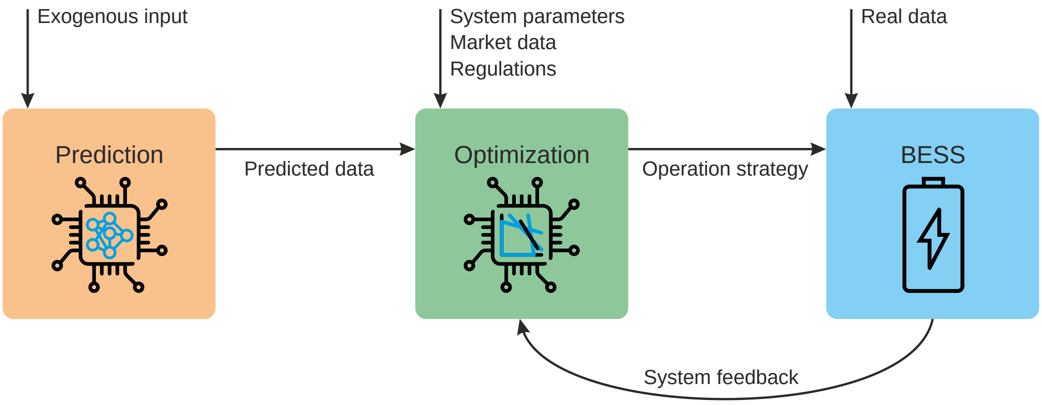

Figure S4: Method to implement the dynamic multi-use optimization on a real-world battery energy storage system (BESS). Prediction data, system parameters, market and regulatory constraints flow into the optimization model, with the prediction data updated at regular intervals. Optimizations are executed with each addition of new information and the strategy implemented on the BESS by the energy management system. System feedback from the BESS to the optimization model serves to improve the interface and adjust parameters to converge them to the real-life values.

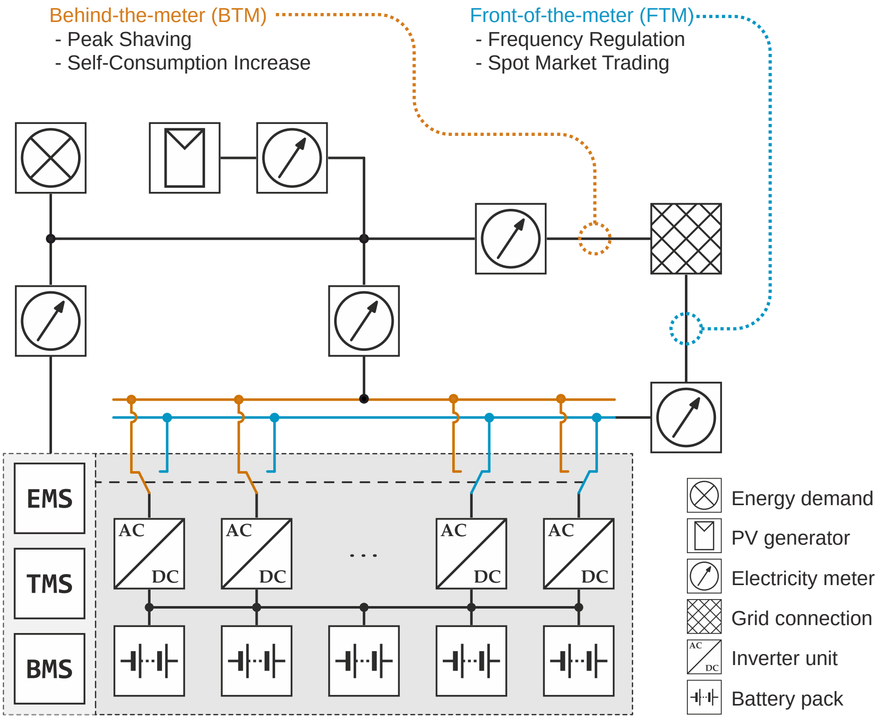

Figure S5: Topology of system power flows differentiating between behind-the-meter (BTM) and in-front-of-the-meter (FTM) applications. The system includes the load, generator, electricity meters, and the battery energy storage system (BESS) (in grey). Included in the BESS are its battery packs, power electronics, and peripheral components, e.g. the energy management system (EMS), thermal management system (TMS), and battery management system (BMS). The orange and blue lines depict how the inverters enable the allocation of storage to either BTM or FTM applications. This process is directed by the BESS's EMS. With an increasing number of inverters, the system flexibility can be increased, which in turn also improves the efficiency of the BESS.[13] Another essential attribute of the system's topology is the direct current busbar connecting the inverters and the battery packs. Each battery pack comprises of several battery cells. Without the busbar, each battery pack would be connected to only one inverter. Thus, the busbar enables flexibility between power and energy constraints in the system.

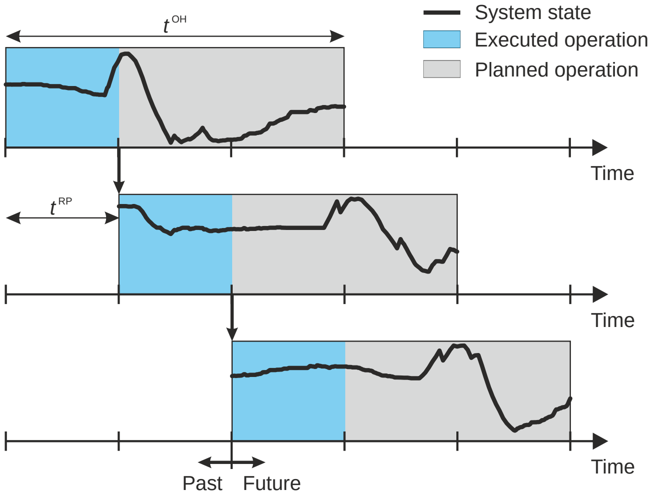

Figure S6: Schematic illustration of the established rolling horizon optimization. The system state, optimized within every optimization horizon t^{OH}, can represent any optimization variable (e.g. state of charge). After each rolling period t^{RP} a new optimization is conducted, leading to multiple re-evaluations of system states from previous optimizations.

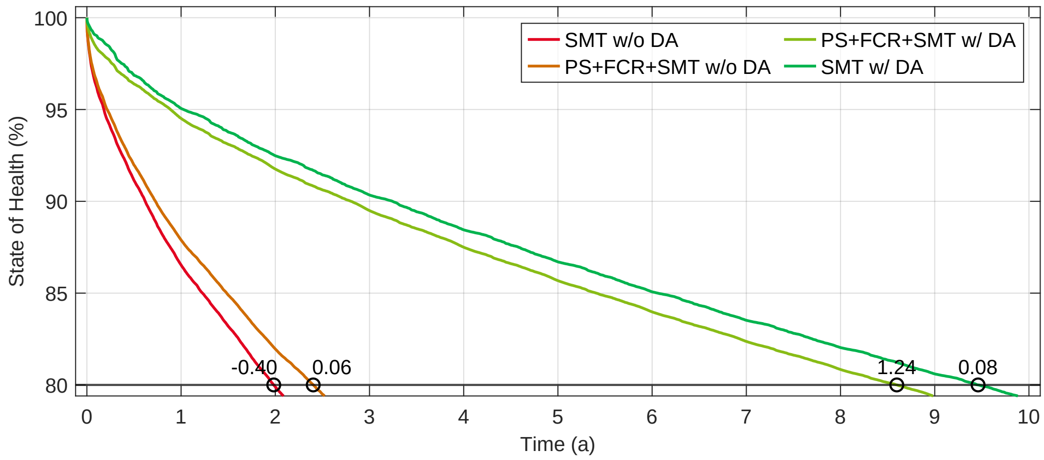

Figure S7: Comparison of state of health development of a battery energy storage system until end of life with and without degradation awareness (DA). The analyzed applications are peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT). Two scenarios are shown, the single-use case with only SMT and the multi-use case with all applications, PS+FCR+SMT, because the SMT application is the one most influenced by the consideration of cycle opportunity costs. Battery degradation awareness in the model ensures that only the most profitable trades are implemented, to avoid undue cycles. The lifetime extending effect of battery degradation awareness is reflected in the significantly higher net present value per EUR invested.

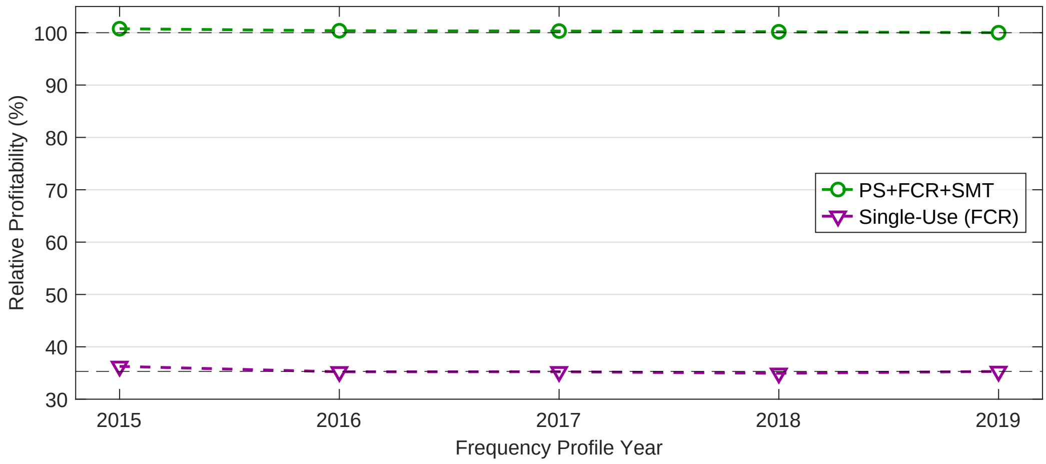

Figure S8: Relative profitability sensitivity analysis depicting the effect of various input frequency profiles. The multi-use scenario, with the peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT) application, is compared with the single-use FCR scenario, as this is the application most sensitive to input frequency. Profitability is shown relative to the multi-use scenario with 2019 data.

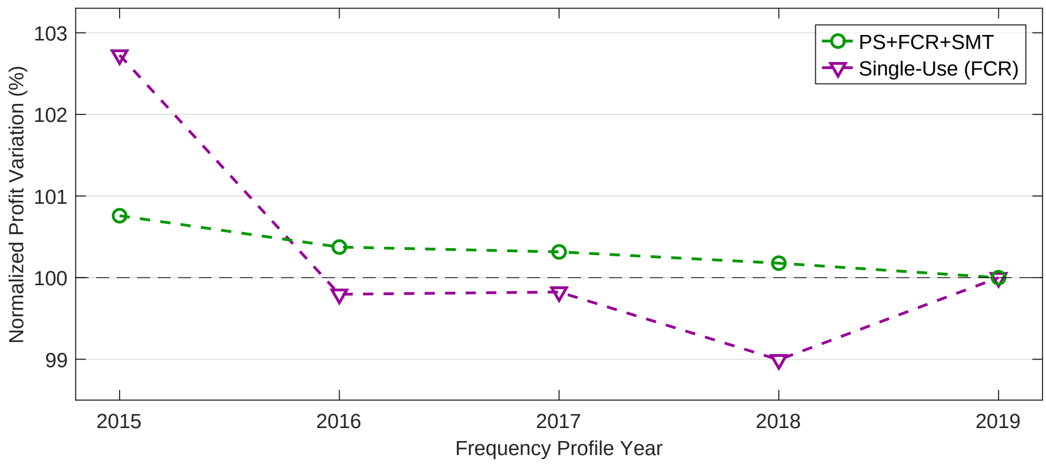

Figure S9: Normalized profit variation comparison of single-use versus multi-use. The multi-use scenario, with the peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT) application, is compared with the single-use FCR scenario, as this is the application most sensitive to input frequency. Profit is normalized to the respective 2019 results. The single-use scenario shows higher sensitivity to different frequency profiles than the multi-use scenario, but overall variation is minimal.

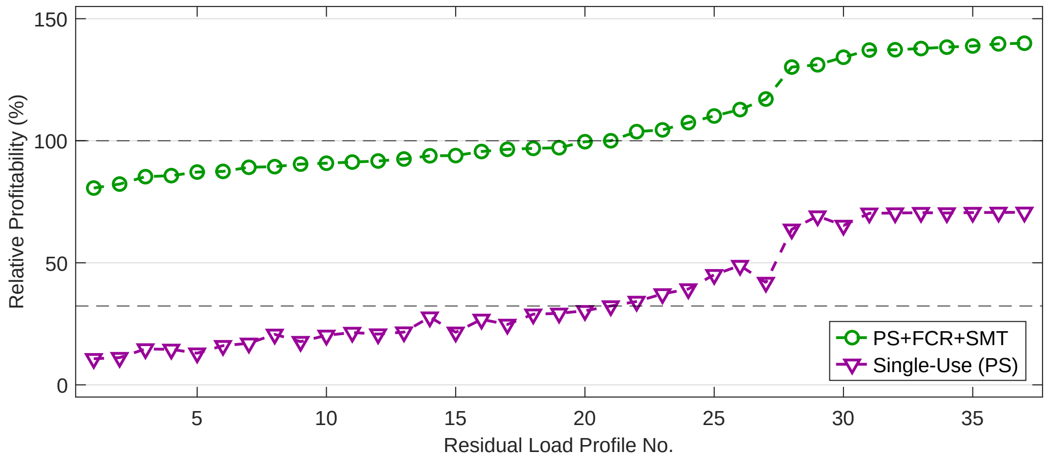

Figure S10: Relative profitability sensitivity analysis depicting the effect of various input residual load profiles from commercial players in Germany. The multi-use scenario, with the peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT) application, is compared with the single-use PS scenario, as this is the application most sensitive to residual load. Profitability is shown relative to the multi-use profitability using the twenty-first residual load profile as a base case, chosen due to its representative results. Gap between single- and multi-use profitability is shown to be quite steady.

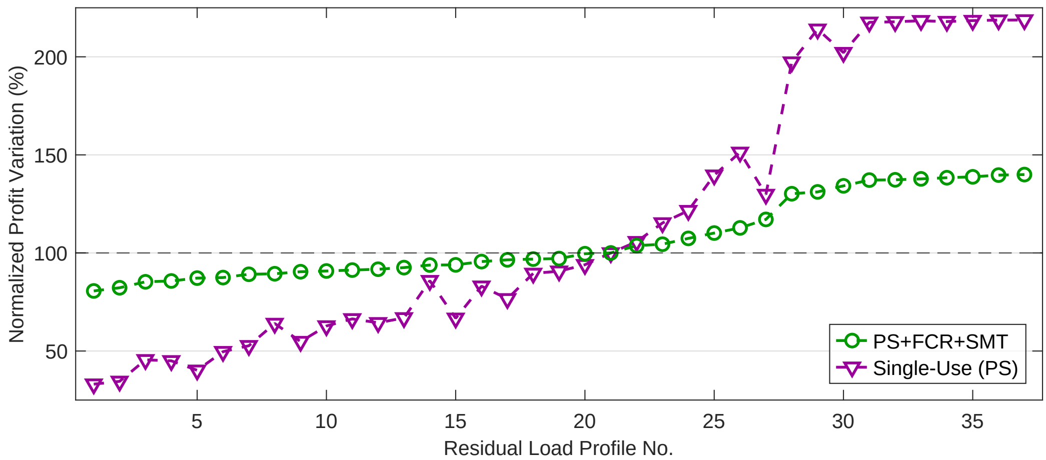

Figure S11: Comparison of normalized profit variation due to residual load profile. The multi-use scenario, with the peak shaving (PS), frequency containment reserve (FCR), and spot market trading (SMT) application, is compared with the single-use PS scenario, as this is the application most sensitive to residual load. Profit is normalized to the respective results using the twenty-first residual load profile (base case, chosen due to its representative results). The single-use scenario shows significantly greater sensitivity to different residual load profiles than the multi-use scenario.

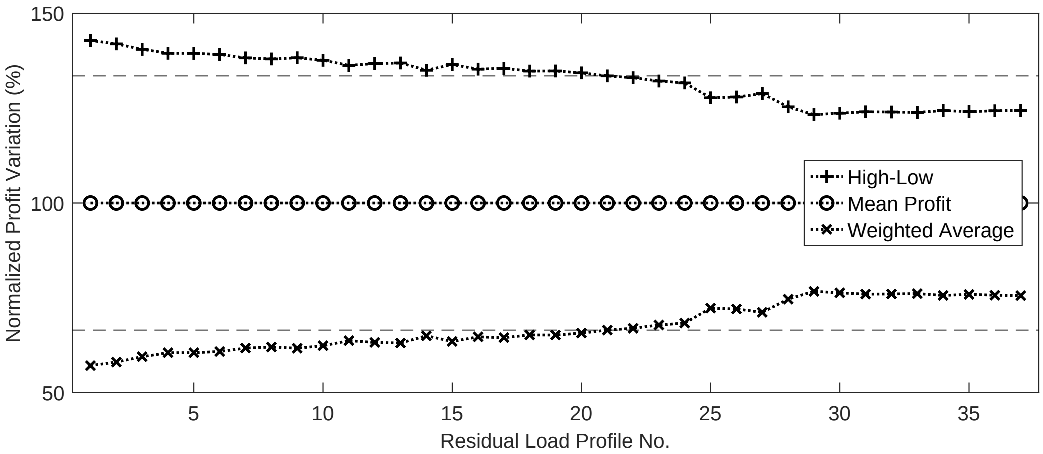

Figure S12: Lower and upper bound of multi-use profitability depending on price signal resolution. The profitability of the multi-use scenario is depicted in dependence of the residual load profiles. The upper bound represents maximum profitability using the high-low price signals from the intraday continuous market. Analogously the lower bound represents the worst case, where the weighted average price is utilized. Profitability is normalized around the mean between the lower and upper bound for each residual load profile. The mean profit of the twenty-first residual load profile (base case, chosen due to its representative results), can vary by ±35 %, depending on implementation success.

Aggregator Model

The aggregator model for the shared revenue from the frequency containment reserve (FCR) application consists of the two equations,

$$\mathrm{k} = \frac{\mathrm{r}^{\mathrm{FCR,max}} \times P^{\mathrm{FCR,rem,max}} - \mathrm{r}^{\mathrm{FCR,min}} \times P^{\mathrm{FCR,rem,min}}}{P^{\mathrm{FCR,rem,max}} - P^{\mathrm{FCR,rem,min}}} \tag{S1}$$

$$\mathrm{d} = P^{\mathrm{FCR,rem,min}} \left(\mathrm{r}^{\mathrm{FCR,min}} - \mathrm{k}\right) \tag{S2}$$

where the ratio of remuneration received by the battery energy storage system's operator ranges from $\mathrm{r}^{\mathrm{FCR,min}} = 60\,\%$ to $\mathrm{r}^{\mathrm{FCR,max}} = 85\,\%$ and the range of FCR power provided is between $P^{\mathrm{FCR,rem,min}} = 100\,\mathrm{kW}$ and $P^{\mathrm{FCR,rem,max}} = 1000\,\mathrm{kW}$.

Despite the degrees of freedom provided by the aggregator, the single-use FCR scenario shows that 1 MW is bid 95 % of the time. Still, only 85 % of generated revenue is received by the storage system operator, showing that the flexibility of the aggregator is not strictly necessary and limiting the profitability of this use case. In the multi-use scenario, the available flexibility is utilized to a greater extent; still 1 MW is bid 70 % of the time. Despite the higher profit potential operating without an aggregator, this implementation is chosen, because it is more realistic for small storages to outsource the risk to an aggregator.

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6 Electric vehicle multi-use

Building on the studies from Section 2.3.6 and Chapters 3 to 5, this chapter presents the paper *Electric vehicle multi-use: Optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context*. As already established for large-scale, stationary storage systems, the *multi-use* operation with EVs is analyzed in this chapter. A German commercial electricity consumer with an EV fleet is defined as the basis for the study. To observe the influence of the fleet size on the operation strategy, the number of EVs is varied between one and 150 vehicles [47].

As in the publication shown in Chapter 5, the following four applications SCI, PS, FCR, and SMT are considered [46]. Due to the requirements for participation in these applications and their markets, it is sometimes necessary to offer certain minimum quantities of power or energy. Although the energy capacities of EVs are steadily increasing, they are usually smaller than those of large-scale stationary units. To meet the requirements of minimum quantities, it is possible to use aggregator models or to accumulate multiple EVs into larger fleets that satisfy the power and energy criteria (cf. Section 2.4.3). Since EVs are primarily purchased for their provision of mobility, this application is considered and prioritized in the model. Compared to the four applications mentioned above, the designed mixed-integer linear programming framework *ev_mu_opt*[5] does not decide how much the mobility provision application should be served. Based on defined driving, parking, and plug-in profiles created with the *emobpy* tool [187], the framework is given hard constraints on when and how the vehicle is used for mobility provision.

Since each of the EVs in the fleet can only serve other applications if it is connected to the energy system, the plug-in times of the vehicles are crucial. During the plug-in periods of an EV, the mobile energy storage behaves similarly to a stationary storage. During these time periods, the EMS of the EV fleet will also behave opportunistically and try to maximize the added value from the individual applications. This in turn means that increased energy throughput accelerates battery cell degradation, which is why opportunity costs for energy throughput are also implemented in this framework. To accurately calculate cell degradation, the optimizer is embedded in the MPC framework together with a semi-empirical degradation model [238]. In contrast to stationary systems, there are no calibrated electricity metering systems available for EVs. However, since the distinction between BTM and FTM applications must also be applied here, the optimization algorithm in the EMS must guarantee that no energy is exchanged between the partitions. This delimitation can lead to complex problems, especially with mobility provision. For example, if the actual energy content of the BTM partition is empty, but there is still energy available in the FTM partition to power the electric motors, the vehicle can be driven from a technical point of view, but from a regulatory point of view, this energy is not allowed to be used for mobility purposes (cf. Section 2.2). To solve this problem, a unidirectional energy flow from FTM to BTM partition is implemented, which allows the stored FTM energy to be used also for mobility provision. This showcases the technical potential over the regulatory hurdles. Since BTM and FTM electricity have different price structures and FTM generally benefits from reduced levies

[5] Code is publicly available at the Gitlab repository: https://gitlab.lrz.de/open-ees-ses/ev_mu_opt

and surcharges [178], it must be guaranteed that the price for FTM electricity used for driving is equal to BTM electricity. For this purpose, the optimization model always tracks how much energy flows from the FTM application to the BTM application, and the necessary levies and surcharges are added in accordance with this energy flow.

As with stationary storage, the study shows that profitability increases over the lifetime of the vehicles as more applications are served. By setting a commercial electricity consumer, the vehicle usage patterns are very similar, which is also reflected in the fleet size results. In the context of heterogeneity, the plug-in period is particularly important, as it is exclusively during this time period that additional applications, apart from mobility provision, can be served.

The combination of technical, economic, and regulatory constraints is a major strength of this research. By establishing a methodology for EV *multi-use*, which shows the cash-flow generating potential of a fleet of EVs, this paper makes an important contribution to research, enabling the transition to electric mobility.

Author contribution Stefan Englberger developed the idea of the study, developed the EV *multi-use* framework, carried out the simulations, and analyzed the data. Kareem Abo Gamra helped to develop the model and analyze the data. Michael Schreiber helped to parameterize the model and develop the regulatory framework. The manuscript was written by Stefan Englberger, Kareem Abo Gamra, and Benedikt Tepe and was edited by Michael Schreiber, Holger Hesse, and Andreas Jossen. All authors discussed the data and commented on the results.

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

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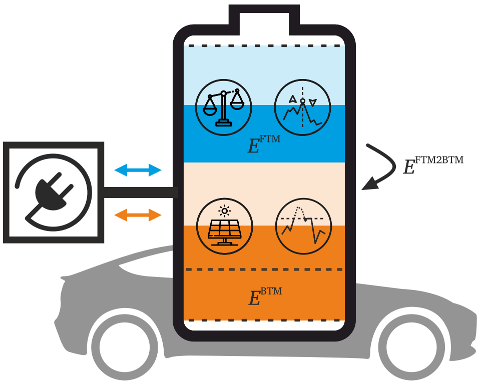
Electric vehicle multi-use: Optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context

Stefan Englberger [a,*], Kareem Abo Gamra [a], Benedikt Tepe [a], Michael Schreiber [b], Andreas Jossen [a], Holger Hesse [a]

[a] Institute for Electrical Energy Storage Technology, Technical University of Munich, Arcisstr. 21, 80333 Munich, Germany

[b] The Mobility House GmbH, St.-Cajetan-Str. 43, 81669 Munich, Germany

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.

* Corresponding author.
E-mail address: stefan.englberger@tum.de (S. Englberger).

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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
$P^{\text{FCR},offer}$	offered power for FCR application
$P^{\text{FCR,reserve}}$	reserve power for FCR application
$P^{\text{FTM,CH}}$	charging power at FTM partition
$P^{\text{FTM,DCH}}$	discharging power at FTM partition
$\text{p}^{\text{BTM,E,purchase}}$	energy-related price for purchased BTM electricity
$\text{p}^{\text{BTM,E,sell}}$	energy-related price for sold BTM electricity
$\text{p}^{\text{BTM,P}}$	power-related price for purchased BTM electricity
$\text{p}^{\text{charges}}$	price charges to shift energy from FTM to BTM partition
p^{FCR}	remuneration price for FCR provision
$\text{p}^{\text{SMT,purchase}}$	price for purchased electricity for SMT application
$\text{p}^{\text{SMT,sell}}$	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].

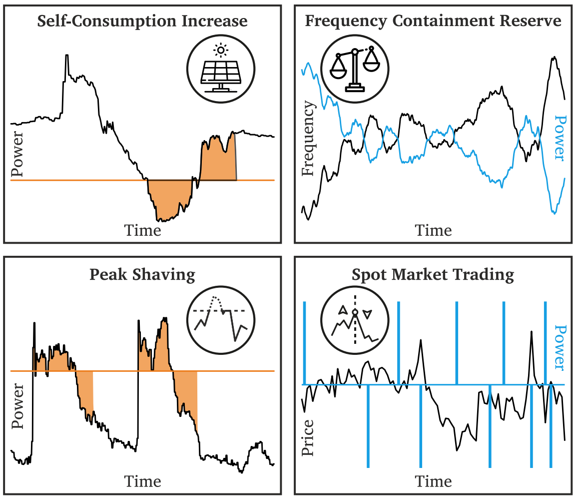

Fig. 1. Schematic illustration of the four grid applications: self-consumption increase (SCI) profits from zero crossings of the residual load. During peak shaving (PS) high load peaks are capped by the energy storage system. Frequency containment reserve (FCR) describes the provision of power to stabilize 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.

$$\begin{aligned} P_t^{\mathrm{FCR,offer}} \cdot t^{\mathrm{FCR,reserve}} &\le E_t^{\mathrm{FTM,actual}} \\ \le E_t^{\mathrm{FTM,usable}} &- P_t^{\mathrm{FCR,offer}} \cdot t^{\mathrm{FCR,reserve}} \end{aligned} \tag{7}$$

$$\begin{aligned} P_t^{\mathrm{FCR,MIN}}(\mathrm{f}_t, \mathrm{f}^{\mathrm{n}}, \mathrm{f}^{\mathrm{DB}}, \sigma, P_t^{\mathrm{FCR,offer}}) &\le P_t^{\mathrm{FCR}} \\ \le P_t^{\mathrm{FCR,MAX}}&(\mathrm{f}_t, \mathrm{f}^{\mathrm{n}}, \mathrm{f}^{\mathrm{DB}}, \sigma, P_t^{\mathrm{FCR,offer}}) \end{aligned} \tag{8}$$

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.

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

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 ($=\mathrm{revenue}-\mathrm{cost}$), 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.

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

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

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

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

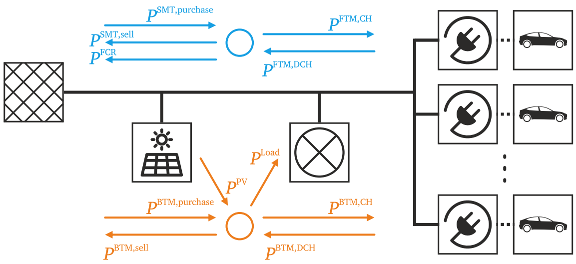

Fig. 2. Illustration of the physical power flows between the grid, photovoltaic (PV) generator, load, chargers, and electric vehicles (EVs). The arrows in orange and blue highlight the node constraints at the behind-the-meter (BTM) and in front-of-the-meter (FTM) partitions.

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].

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

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

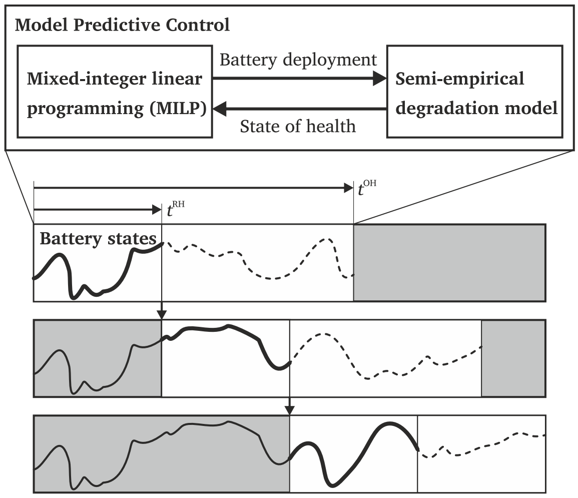

Fig. 3. The mixed-integer linear programming (MILP) algorithm and the semi-empirical degradation model are embedded in the model predictive control (MPC) framework. Within the MPC framework, the battery deployment and state of health (SOH) of the electric vehicles (EVs) are calculated and exchanged. 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:

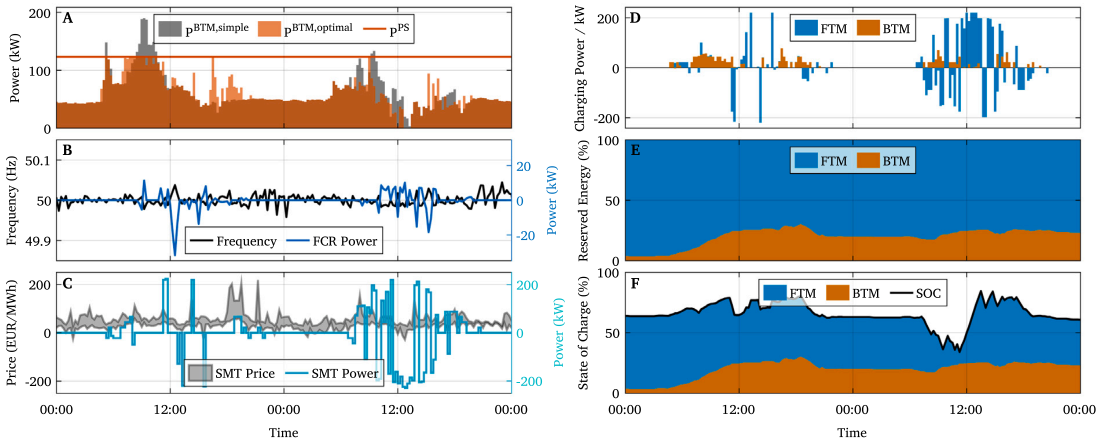

Fig. 4. Optimization framework outputs of an *EV multi-use* operation strategy with SCI, PS, FCR, and SMT. A two day excerpt is shown for: **A** the residual load on the BTM partition and the respective PS threshold; **B** grid frequency input profile and the FCR power provided by the EV fleet; **C** 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.

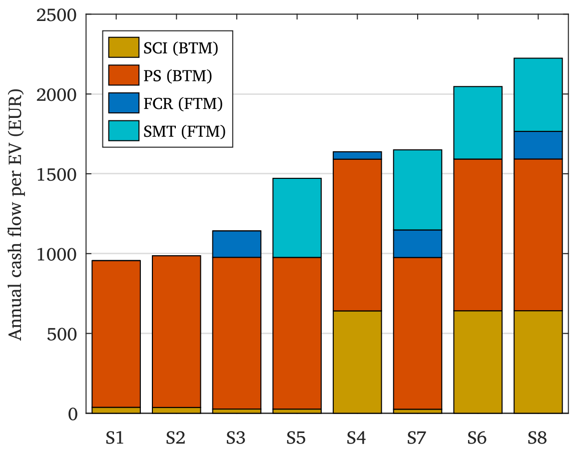

Fig. 5. Annual cash flow increase per electric vehicle (EV) compared to reference scenario *S0*. Here, the fleet size is 10 EVs.

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

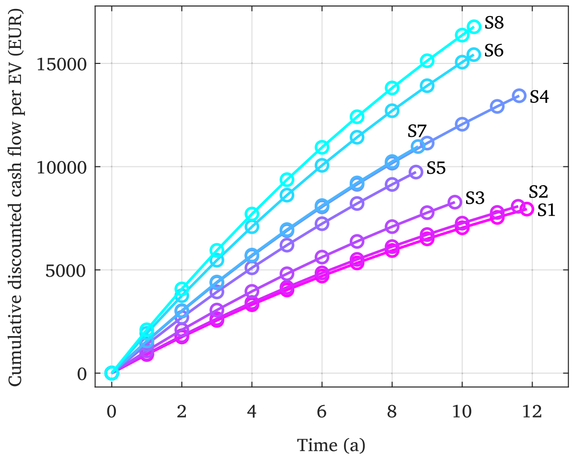

Fig. 6. Discounted cash flow increase per electric vehicle (EV) compared to reference scenario *S0*. Here, the fleet size is 10 EVs and a degradation aware operation strategy is applied.

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

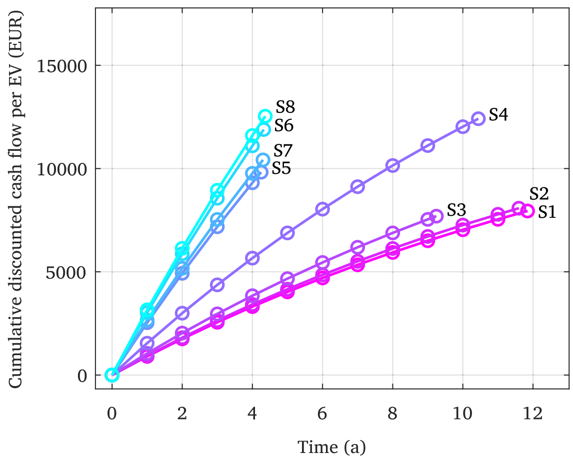

Fig. 7. Discounted cash flow increase per electric vehicle (EV) compared to reference scenario *S0*. Here, the fleet size is 10 EVs and the model does not consider the opportunity costs per cycle when determining the optimal operation strategy.

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].

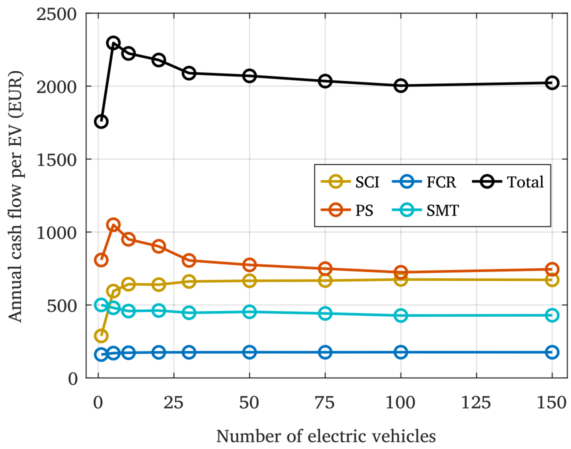

Fig. 8. Annual cash flow contribution per application and electric vehicle (EV) for scenario *S8*. Here, the numbers represent the cash flow increase compared to the reference scenario *S0*.

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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7 Conclusion and outlook

7.1 Conclusions

Accelerating the deployment of battery energy storage is at the center of the sustainable transformation of future energy systems. To overcome the challenge of limited investment attractiveness, two energy management approaches – *multi-use* and *multi-storage* – are developed in this thesis and evaluated using linear optimization. Along with boosting the profitability of the analyzed storages, the methods aim to closely integrate the technical considerations, such as battery degradation, to enable a well-rounded, techno-economic study.

As the transition in the energy sector is progressing in all areas, including residential – a household with PV generator, home energy storage, and EV is presented in Chapter 3. Through the investigation of the household's optimized power flows the significant economic advantage of up to 15 % OPEX reduction of optimized unidirectional EV charging is demonstrated. The extension to bidirectional charging brings about a further 11 % cost reduction. In contrast to this economic improvement, the higher energy throughput in the scenario with bidirectional charging leads to a greater stress on the energy storage. This, in turn, reduces battery lifetime by 12 %. Proportionally to the available flexibility in the household, the self-generated power of the PV generator is used more effectively, which increases the self-consumption and self-sufficiency rates. Techno-economic analysis reveals that in a scenario with bidirectional EV charging, self-consumption improvements with and without a stationary storage range between 160 EUR and 1,381 EUR savings over ten years. Depending on the degree of flexibility provided by the EV, i.e. for vehicles with high plug-in times, the home energy storage can become obsolete, as the added value of the stationary storage does not justify its investment cost.

Building on the findings at the household level, Chapter 4 combines peer-to-peer trading and home energy management to allow simultaneous optimization on both a household and community level. The presented mechanism is applied to a network of multiple households with flexibilities in the form of both stationary and mobile storage systems. To evaluate the impact of the flexibilities on the household and community, a distinction is made between decentralized and central energy management. The study shows that for the decentralized decision-making approach, the degradation effects of the storage systems are not negatively affected by the existence of a local electricity market, as the same operation strategies for the flexibilities are determined, regardless whether one exists or not. The central approach yields superior economic results especially for small communities, as more information is available to the central EMS, the *multi-storage* network is optimized at the community level, and the broader heterogeneity of the households allows for more synergies to be exploited. The share of locally traded electricity, a metric of the peer-to-peer market effectiveness, saturates at a network size around 20 households and reaches over 10 %, 20 %, and 35 % in the decentral, central with unidirectional, and central with bidirectional charging scenarios, respectively. The central approach is preferable if users value independence from electricity retailers, and the decentralized approach may be favorable to a community that values control over its flexibilities.

In Chapter 5, the method of *multi-use* with a large-scale stationary storage system is evaluated. The evaluation implements a model predictive control framework, which combines a mixed-integer linear programming algorithm with a semi-empirical degradation model. The study shows that application stacking boosts investment attractiveness. Through the investigation of several behind-the-meter (BTM) and in front-of-the-meter (FTM) applications, it is shown that the profitability increases proportionally with the number of stacked applications. Whereas the profitability indices of the investigated single-use scenarios range between 4 % and 18 %, the *multi-use* scenarios reach values between 63 % and 124 %. Using the topology shown in the study, the *multi-use* approach complies with both technical and regulatory conditions by keeping BTM and FTM partitions separated. When comparing different *multi-use* types, the dynamic *multi-use* approach proves to be superior, as it allows for the most flexible allocation of power and energy over time. The optimized battery utilization yields significant economic benefits but also leads to accelerated degradation of the battery cells. Particularly for energy throughput-intensive applications, such as spot market trading, the study shows that degradation aware energy management brings a great benefit to the energy storage and its stakeholders by increasing battery lifetimes from around two to almost ten years.

As the energy capacity of modern EVs continues to grow, so does the techno-economic potential of an extension of the *multi-use* approach to these mobile storages. Chapter 6 shows how the stacking of applications on an EV fleet increases profitability for the fleet operator and EV owner. Analogously to stationary storage, the evaluation shows that deployment flexibility and application synergies increase as more applications are served. Due to the consuming nature of mobility provision, the results show that BTM applications are particularly interesting. As in Chapters 3 and 4, it is confirmed here that significant added value of up to 956 EUR/a and 2,224 EUR/a can be generated by optimizing unidirectional and bidirectional charging, respectively. However, the additional operation of applications when an EV is plugged-in can also lead to added stress in the battery cells, which in turn results in higher degradation losses and reduced lifetime. The inclusion of degradation awareness in the optimizations helps to actively avoid unfavorable operation strategies. This leads to slightly reduced annual cash flows but significantly prolongs battery lifetime and thereby investment attractiveness. Due to the technical setup of EVs and their grid connection, it is more complex to separate BTM and FTM applications and their energy. By focusing on the role of the energy management system (EMS), the presented methodology dispenses the need for calibrated electricity meters.

7.2 Potential future research

To support the deployment of battery storage and further drive the *multi-use* and *multi-storage* approaches presented in this thesis, there are several topics that should be focused on in subsequent studies.

As this work utilizes deterministic optimization, the algorithm is gifted with perfect foresight, albeit only for a limited time period. Thus, the model predictive control framework is well-suited to handle prediction data, even error prone prediction data. This lays the foundation upon which future research can increase the scope on data prediction and its effect on the energy management for battery storage. In addition, the optimization approach can be adjusted to other approaches, such as non-linear algorithms or meta-heuristics. This would enable the modeling of non-linear processes in the battery storage and overall energy system. Currently, the algorithm for degradation awareness only considers the energy throughput. This can be extended to include state of charge and C-rate dependencies, which would lead to increased complexity and computational demand. However, with growing computational power, future battery energy storage control systems could be capable of handling such complex algorithms.

With the swiftly changing nature of battery technology research, continuous improvements are a given. This means that the energy management of battery storage needs to be continuously updated to reflect state-of-the-art technologies. Therefore, it is recommended that the presented methodologies are extended to new technologies and validated using the relevant, applicable models for the battery and its internal processes, such as capacity fade.

Beside the modeling of battery storage, real-world implementation is needed to validate the findings and establish proof-of-concepts in a variety of local environments. For instance, the testing of complex EMSs' applicability, including implemented data prediction and optimization procedures can be highly beneficial to boost the proliferation of sophisticated EMS applications. In addition, a real-world implementation of EV *multi-use*, where the EMS distinguishes between BTM and FTM value streams and replaces the need for calibrated electricity meters, is required for the proof-of-concept. This thesis focuses on regulatory conditions in Germany, however, for a global validity the presented methodologies should be adjusted and applied to multiple, diverse locations.

For the EVs considered in this thesis, the OPEX but not CAPEX are taken into account. In addition, only revenues of the added applications are included. The added value from mobility provision was defined as out of scope, as it is highly subjective to the individual user and thus difficult to quantify. For additional research to develop a quantification methodology to include this value stream, as well as the CAPEX in the investment attractiveness calculation, would give a more complete picture.

Additionally, the scope of this work is focused on closed energy systems on a consumer or community level and the interaction with or effects on the grid are not examined. For further research the effect of battery energy storage on the grid operation and distribution system, especially of EVs, will give insight into the effect of storage on the greater electricity network, and the role that the EMS can play.

Overall, this thesis is a milestone in the research for *multi-use* and *multi-storage*, as it provides a research foundation that enables practical implementation, which can be expanded upon and needs to be validated via real-world use cases.

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Supervised student theses

a Gnacy, M.: *Reactive power compensation with the help of a stationary battery storage (German: Blindleistungskompensation mit Hilfe eines stationären Batteriespeichers)*, Research seminar, 2018

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k Abo Gamra, K.: *Evaluation of Multi-Use Strategies with Electric Vehicles*, Master's Thesis, 2021

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