Applied Energy 374 (2024) 123995

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

# Optimizing electric vehicle fleet integration in industrial demand response: Maximizing vehicle-to-grid benefits while compensating vehicle owners for battery degradation

Andre Leippi [a,b], Markus Fleschutz [a,d], Kevin Davis [a], Anna-Lena Klingler [c], Michael D. Murphy [a,*]

[a] Department of Process, Energy and Transport Engineering, Munster Technological University, Bishopstown, Cork, Ireland
[b] Institute of Human Factors and Technology Management IAT, University of Stuttgart, Stuttgart, Germany
[c] Fraunhofer IAO - Institute for Industrial Engineering, Stuttgart, Germany
[d] Entelios AG, Munich, Germany

ARTICLE INFO

*Keywords:*
Electric vehicle fleet
Demand response (DR)
Vehicle-to-grid (V2G)
Battery degradation
Multi-objective optimization
Electric vehicle performance characteristic

ABSTRACT

This paper addresses the integration of electric vehicle (EV) fleets into industrial smart grids to increase operational flexibility. It focuses on an extended multi-objective optimization problem that minimizes two primary objectives: (i) the electricity expenditure of a company using its employees' EV batteries as temporary distributed energy storage, and (ii) the costs associated with the degradation of EV batteries, given the additional usage from the company's perspective. In this paper, the utilization of an EV fleet is simulated at the individual car level over a one-year period. These optimization problems were balanced by using real-time electricity prices and the effective demand response (DR) of the company's electrical load. The company utilized the EVs as battery storage to offset fluctuating electricity prices, while compensating EV owners with free electricity for the costs incurred through degradation of their batteries. The extent to which the company could compensate EV owners while maintaining the viability of vehicle-to-grid (V2G) services in a non-residential scenario was explored. The results established an equilibrium point at which the financial benefits for the company resulting from V2G services was maximized against the negative financial impact of increased battery degradation for EV owners. The results showed that there is a potential mutual benefit between the company and EV owners, even if the company provided EV owners with free charging (based on a percentage of their battery capacity) for each day of their attendance. This mutually beneficial zone ranged from 3%–10% of the battery capacity for AC charging and 6%–17% for DC charging. Optimal Pareto values indicated an economic trade-off that benefited both stakeholders, with DC charging proving significantly more profitable for the company than AC charging (between 257.5% to 38.1% depending on the amount of free charging provided). The findings emphasize the need for an equitable pricing mechanism considering the different characteristics of EVs based on the operational and financial benefits for both parties to create a balanced pricing framework for V2G.

## 1. Introduction

### 1.1. Motivation

Today's transportation industry is undergoing a profound transformation. Marked by record growth in EV sales, including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), which increased by 55% in 2022 compared to 2021, to over 10 million units sold worldwide [1]. Given the ratio of EV sales to total vehicle sales increased from 9% in 2021 to 14% in 2022, a very substantial increase can be observed in the growth of EV sales [1]. This shift from internal combustion engine vehicles to electric mobility offers a promising opportunity to address environmental challenges and the need for clean energy solutions. The EU Commission's ambitious targets for vehicle emissions and the ambitious goal of zero emissions from new cars by 2035, underscore the growing global trend towards low, and zero-emission vehicles [2]. Given the large number of EVs parked at company's car parks, the possibility of using the storage capacity of EV batteries via vehicle-to-grid (V2G) or vehicle-to-building (V2B) systems offers a compelling prospect. Accordingly, EV fleets could be considered as a battery swarm that temporarily takes the function of

* Corresponding author.
*E-mail addresses:* andre.leippi@mycit.ie (A. Leippi), MichaelD.Murphy@mtu.ie (M.D. Murphy).

https://doi.org/10.1016/j.apenergy.2024.123995
Received 9 January 2024; Received in revised form 3 July 2024; Accepted 20 July 2024
Available online 1 August 2024

**Nomenclature**

**Acronyms/abbreviations**

| | |
|---|---|
| BDC | Battery degradation costs |
| BES | Battery energy storage |
| BEV | Battery electric vehicle |
| C-rate | Charging rate |
| CS | Charging station |
| DOD | Depth of discharge |
| DR | Demand response |
| DRAF | Demand response analysis framework |
| DSM | Demand side management |
| EEG | German renewable energies act |
| EG | Electricity grid |
| EOL | End of life |
| ESS | Energy storage system |
| kWh | Kilowatt-hour |
| MIC | Maximum import capacity |
| MILP | Mixed integer linear programming |
| MOO | Multi-objective optimization |
| PHEV | Plug-in hybrid electric vehicle |
| PV | Photovoltaic |
| RES | Renewable energy sources |
| RTP | Real-time pricing |
| SC | Smart charging |
| SOC | State of charge |
| TCC | Total company's cost |
| TOU | Time-of-use |
| V2B | Vehicle-to-building |
| V2H | Vehicle-to-home |
| V2X | Vehicle-to-everything |

**Symbols**

| | |
|---|---|
| $\Delta t$ | Time step, 15 min |
| $\eta^{\mathrm{self}}$ | Self-discharge of the electric vehicle |
| $\eta_i$ | Efficiency of the on-board charger for EV i |
| $\lambda^{\max}$ | Maximum EV battery capacity limit (kWh) |
| $\lambda^{\min}$ | Minimum EV battery capacity limit (kWh) |
| $E^{\mathrm{EV}}$ | EV Battery capacity (kWh) |
| $\alpha$ | Pareto weighting factor |
| $\alpha^{c}_{t,i}$ | Battery degradation coefficient at time $t$ for EV $i$ |
| $\bar{E}^{\mathrm{EV}}_{i}$ | Average SOC of the $i$th EV during battery utilization |
| $\beta_1 \rightarrow \beta_8$ | Fitting parameters of the battery degradation model |
| $\pi_t$ | Real-time pricing at time $t$ |
| $\varphi$ | Normalization factor |
| $C^{\mathrm{Bat}}$ | Capital cost of the battery [€/kWh] |
| $C^{\mathrm{EG,NF}}$ | Network fees for purchased electricity |
| $C^{\mathrm{TOT}}_{\mathrm{argmin}}$ | Total costs to be minimized |
| $c^{\mathrm{EG,buy}}_{\mathrm{peak}}$ | Peak price for buying electricity |
| $C^{\mathrm{deg}}_{t,i}$ | Battery degradation cost per time interval at time $t$ |
| $C^{\mathrm{EG,addon}}_{t}$ | Time-independent fixed energy price |
| $C^{\mathrm{RTP}}_{t}$ | Dynamic RTP |
| $CR^{\mathrm{EV}}$ | C-rate of the EV |
| $E^{\mathrm{EV,cap}}$ | Maximum EV battery capacity |
| $E^{\mathrm{EV}}_{t,i}$ | Stored energy of the $i$th EV at time $t$ |
| $E^{\mathrm{exch}}_{t,i}$ | Amount of electricity exchanged by the $i$th EV at time $t$ |
| $P^{\mathrm{EG,MIC}}$ | Maximum import capacity of the grid |
| $P^{\mathrm{EG,dem}}_{t}$ | Electricity demand of the company at time $t$ |
| $P^{\mathrm{EG,sell}}_{t}$ | Grid electricity sell quantity at time $t$ |
| $P^{\mathrm{EV,ch}}_{t}$ | Charging of EV (kW) |
| $P^{\mathrm{EV,dis}}_{t}$ | Discharging of EV (kW) |
| $P^{\mathrm{EG,buy}}_{\mathrm{peak}}$ | Annual peak power for buying |
| $P^{\mathrm{EG,consumpt}}_{t}$ | Electricity consumption at time $t$ from the grid |
| $T^{\mathrm{Bat}}$ | Battery temperature of the EV |
| $y^{\mathrm{EV,ch}}_{t,i}$ | Decision variable for charging |
| $y^{\mathrm{EV,dis}}_{t,i}$ | Decision variable for discharging |
| i | Current electric vehicle |
| N | Total number of time steps |

a stationary battery storage to provide the necessary storage capacities and balance the fluctuations of supply and demand. This could facilitate ancillary services such as peak shaving and grid stabilization, rewarding EV owners for their participation while increasing the operational flexibility of smart grids and the company's flexibility. According to [3], EVs that are V2G-capable and have a high charging capacity, are highly suitable to create economic benefits. Especially in a non-residential environment, a large EV fleet could become a key demand-side resource for a company's smart grid infrastructure to provide demand response (DR). Traditionally, DR systems have been accessible mainly to the industrial sector [4]. Due to the considerable size of industrial plants and the presence of sophisticated information technology infrastructure, industrial DR promises effective implementation and application of V2G/V2B [5]. Hence, innovative strategies and novel concepts are essential for enhancing the economic and environmental effectiveness of the growing EV supply. Ultimately, the adoption of V2G and V2B technologies not only provides grid stability [6], but also opens economic opportunities for EV owners in the form of free or subsidized charging facilities at work, making the transition to electric mobility even more attractive and sustainable.

### 1.2. Literature review

There is extensive literature, assessing the potential of Vehicle-to-Everything (V2X) concepts, especially Vehicle-to-Home (V2H) studies. These focus on home energy management systems in the context of a home microgrid [7–13]. However, in this paper, only studies on V2G/V2B technologies, outside of exclusively residential scenarios, are considered to address research gaps. By focusing on non-residential buildings, such as commercial buildings, office complexes, car parks, etc., we hope to gain new insights from these systems, as the potential for scalability and flexibility in this context is more far-reaching than in residential scenarios. As a proof-of-concept, this work is intended to provide the basis for future research in this promising and rapidly evolving field of electric mobility.

Table 1 provides a comprehensive comparison of recent studies in this field, categorized based on framework, objective, methodology, compensation for EV owners, as well as time horizon and time resolution of the considered simulation.

**Table 1**
Comparison of the proposed method to similar studies.

| Study | Framework | Objectives | DR program | Compensation for EV owner | Main load | Analysis of EV characteristics | Deg | Time horizon/ resolution |
|---|---|---|---|---|---|---|---|---|
| [14] | V1G | Peak shaving and valley filling | x | x | ✓ | x | x | 24 h/15 min |
| [15] | V1G | Valley Filling, reducing peaks | ✓ | x | x | x | x | 24 h/1 h |
| [16] | V1G | Minimizing the Peak, demand charge and energy cost | ✓ | x | ✓ | x | x | 1 week/15 min |
| [17] | V1G | Maximizing the utilization of PV generation through SC | ✓ | x | x | x | x | 24 h/15 min |
| [18] | V2G | Evaluating the impact of charging strategies and V2G schemes on EV battery Deg | x | x | x | x | ✓ | 24 h/1 s |
| [19] | V2G | Maximizing the use of the local energy and minimizing the power sold to the grid | x | x | ✓ | x | x | 24 h/1 h |
| [20] | V2G | Minimizing the peak power consumption of building | x | x | ✓ | x | x | 24 h/10 min |
| [21] | V2B | Reducing the peak and minimizing the amount of power imported from the grid | x | x | ✓ | x | x | 24 h/5 min |
| [22] | V2G | Maximizing the use of PV energy for EV charging | x | x | x | x | x | 1 year/1 min |
| [23] | G2V, V2B | Benefits of EVs in smart grids, focusing on DSM | ✓ | x | ✓ | x | x | n/a |
| [24] | G2V, V2G | Flattening the peak load and minimizing the daily total cost | ✓ | x | ✓ | x | ✓ | 24 h/1 h |
| [25] | V2G | Minimizing the total cost of the charging station (CS) | ✓ | x | x | x | x | 11 h/30 min |
| [26] | V2G, G2V | Minimizing total cost, increasing PV self-consumption | ✓ | x | x | x | ✓ | 24 h/15 min |
| [27] | V2G | Minimizing the total operation cost | ✓ | x | ✓ | x | ✓ | 24 h/1 h |
| [28] | V2B, B2V | Minimizing the daily electricity cost | ✓ | x | ✓ | x | x | 24 h/1 h |
| [29] | V2G | Reducing the peak pressure of the public grid | ✓ | x | x | x | x | 14 h/n/a |
| [30] | V2G | Minimizing the total cost of charging the EVs, feeding PV power and offering reserves | ✓ | ✓ | x | x | ✓ | 24 h/15 min |
| [31] | V2G | Maximizing the workplace charging station owner's profit | ✓ | ✓ | x | x | ✓ | 24 h/1 h |
| [32] | V2G, V2H | Reducing energy cost of the end-users, decreasing the peak load demand | ✓ | ✓ | ✓ | x | ✓ | 24 h/n/a |
| [33] | V2G | Minimizing the total cost of an intelligent parking lot operation | ✓ | ✓ | x | x | x | 24 h/1 h |
| [34] | V2G | Maximizing profit from price-based energy arbitrage | ✓ | ✓ | x | x | ✓ | 1 year/1 h |
| [35] | V2G | Maximizing the revenues by an EV aggregator through the trading of electricity | ✓ | ✓ | x | x | x | 1 week/1 h |
| [36] | V2G | Minimizing the total operational costs and emissions | ✓ | ✓ | x | x | x | 24 h/1 h |
| [37] | V2G, V2B | Minimizing the total cost of electricity for the building and cost of charging the EVs | ✓ | ✓ | ✓ | x | ✓ | 3 months/ 15 min |
| [38] | V2B | Minimizing the total energy cost of the building | ✓ | ✓ | ✓ | x | x | 24 h/1 h |
| [39] | V2G | Evaluating the potential of peak shaving and valley filling | ✓ | ✓ | ✓ | x | ✓ | 24 h/1 h |
| [40] | V2G | Maximizing profit to each EV owner | ✓ | ✓ | ✓ | x | ✓ | 24 h/1 h |
| [41] | V2G | Minimizing the total operation costs of the microgrid | ✓ | ✓ | ✓ | x | x | 24 h/1 h |
| [42] | V2G | Minimizing the total cost of electricity and the penalty cost of wasting renewable power | ✓ | ✓ | ✓ | x | x | 7 days/30 min |
| [43] | V2G | Maximizing profitability for the buildings, and fleet of EVs | ✓ | ✓ | ✓ | x | x | 24 h/1 h |
| [44] | V2G | Minimizing the total cost of the building and the revenue from discharging EVs | ✓ | ✓ | ✓ | x | ✓ | 1 month/ 1 h |
| [45] | V2G | Limiting the impact of the PHEV's charging and maximize the utilization of the PV | ✓ | ✓ | ✓ | x | x | 9 h/6 min |
| [46] | V2G | Minimizing grid fluctuation, maximizing RES utilization and benefits for EV users | ✓ | ✓ | ✓ | x | x | 1 month/ 15 min |
| This study | V2G, V2B | Minimize the energy cost of a company vs the degradation costs of the EV batteries | ✓ | ✓ | ✓ | ✓ | ✓ | 1 year/15 min |

V1G = unidirectional smart charging; Deg = Degradation (battery degradation was considered in the study).

In [47], the literature regarding EV battery usage in non-residential DR scenarios considering battery degradation was reviewed. The results showed there is a lack of V2G studies that comprehensively consider DR and battery degradation in EV charging scenarios and balance it with financial compensation for EV owners. It was also found that when considering degradation of EV batteries in optimization scenarios, degradation models should be used that include several external influencing factors (battery temperature, charging-rate (C-rate), state-of-charge (SOC) or depth-of-discharge (DOD)).

The authors of [14–17] each addressed important aspects of EV charging, proposed methods for peak shaving and valley filling, adjusting EV charging schedules to balance the load on the power grid. However, their framework was only designed for a unidirectional system (V1G). The authors of [16] focused on peak shaving and energy costs, suggesting a controlled charging approach to manage the impact of EV charging on the power grid. The maximization of photovoltaic (PV) generation utilization was achieved in [17] through smart charging (SC) of EV fleets. Other studies used a V2G/V2B framework to investigate the potential of bidirectional charging, but did not consider varying electricity prices such as a time-of-use (TOU) or real-time-pricing (RTP) tariff [18–22]. The authors of [20] showed that the peak power consumption of a building can be minimized using V2G. It was demonstrated that the effectiveness of peak shaving and valley filling depends on the number of available parking spaces for EVs and that the reduction of peak power consumption is not linearly dependent on the number of occupied parking spaces. In [21], peak power was reduced, and the electricity imported from the grid was minimized. The study proposed a dual-tracking control problem for a smart building integrated with a microgrid and a V2B-based DR system. The authors of [22] maximized the use of PV energy from a solar-powered charger with V2G technology for workplace EV charging. In [23], detailed research was presented on the use of EVs as distributed energy resources in the smart grid, which can serve as a controllable load in a power grid depending on the demand. The results showed the feasibility of the proposed concept for demand-side management (DSM). They suggest that with enough EVs available, the bundled batteries could be used to meet the electricity demand of a typical building and generate revenue.

Studies [24–29] addressed the integration of EVs and PV into energy and mobility systems when considering dynamic electricity prices in a V2G/V2B framework. However, direct financial compensation to EV owners due to additional battery degradation from V2G and V2B was not included in these studies. The studies [30–33] included a V2G framework, dynamic pricing, renewable energy sources (RES), and financial compensation for EV owners for participating in V2G services. However, all these studies simulated a time frame of only one day. In [31], a new single optimization mixed integer linear programming (MILP) framework was proposed to coordinate the charging of multiple EVs based on the day-ahead electricity price parked at a workplace charging station equipped with PV. However, a static battery degradation value of €0.032/kWh was assumed, and a main load profile of a building was not simulated, which limits the flexibility of V2G services. In [33], an intelligent parking lot with PV, distributed generators, and a bidirectional grid connection was presented for stochastic charging and discharging scheduling of 500 EVs. The owners of the EVs could make a profit by discharging their EVs and receiving additional incentive payments for providing reserves while having the desired SOC at the departure time. However, battery degradation was not considered in this study.

The studies [34–46] considered compensation for EV owners in addition to the bidirectional framework and the DR program, but have not investigated the impact of different EV characteristics. Study [34] focused on maximizing profit through price-based energy arbitrage by using EVs as network batteries. Considering a battery degradation model and German day-ahead pricing signal for 2019, 123.28 €/EV/year could be generated for a 24 kWh battery. The study in [35] investigated the optimal business case for the provision of grid services by EVs with V2G capabilities. In study [36], a multi-criteria planning method is proposed for operational planning of a large number of EVs in an intelligent distribution system to minimize operating costs and carbon emissions. The EV owners received an incentive price for discharging their vehicles, ignoring battery degradation. An optimization model for collaborative charging with V2B technology that was beneficial to both the campus and EV owners in a regulated electricity market was presented in [37]. This model allowed EV batteries to be charged for free while reducing the campus electricity bill. However, a static price for battery degradation was applied for the simulation in [37]. In [38], an optimal charging and discharging approach for PHEVs was proposed, which aimed to minimize the peak load and the total energy cost. Studies [39,40] focused on optimizing charging infrastructure and planning. Huang et al. [39] examined the economic impact of V2G technology in the workplace, especially with regards to peak shaving and valley filling. The authors of [40] presented models for optimal scheduling of EV charging and discharging in parking lots to maximize revenue for EV owners and maximize EV penetration.

Despite a growing body of research on V2X concepts, particularly in the context of V2G and V2B technologies, there is a noticeable gap in evaluating the impact of individual EV characteristics on profitability outcomes for companies providing V2G services or EV owners receiving free or subsidized charging. To the best of the authors' knowledge, no study has conducted an in-depth investigation of the relationships between EVs' C-rate and battery capacity and the profitability of DR in V2G services. Such an investigation could provide valuable insights for optimizing charging and discharging strategies, especially in non-residential buildings such as factories, retail spaces, or office building complexes, as these offer greater potential for scalability and flexibility than residential properties. Assessing the effects of C-rate and battery capacity on profit, would also help to gain a better understanding of the financial implications for both V2G providers and EV owners who benefit from free or subsidized charging. Therefore, this area of research deserves further exploration and analysis to enable more informed decisions in the emerging field of electromobility and to find equitable compensation approaches for battery degradation as a function of EV characteristics.

As illustrated by the literature review and the analysis in Table 1, the main research gaps in the field of non-residential V2G optimization can be summarized as:

- Holistic solution: lack of simultaneous optimization of the critical objectives of the different stakeholders (company and EV owners) based on RTP and the effective DR of the company's electrical load. None of the previous studies have addressed the trade-off, optimization of energy costs for the company and battery degradation of EVs in a non-residential scenario.
- Compensation models for EV owners: There is a need to explore and formulate new V2G or V2B compensation strategies for EV owners. Most studies lack a detailed trade-off of this critical aspect that may affect the acceptance and adoption for EV owners of these technologies.
- AC vs. DC charging: Investigating the impact of AC and DC charging on economic profitability for companies and EV owners represents a gap within the current field of V2G studies.
- Comparison of EV characteristics: There is a significant gap in the literature regarding the systematic comparison of EV characteristics in DR scenarios that examines the correlations between C-rate and battery capacity, and their respective effects on the economic viability of V2G services, as well as the financial implications for EV owners receiving incentive-based charging schemes.
- Long-term effect studies: Most studies have looked at relatively short time horizons (daily or weekly). More research is needed to understand the long-term impacts and benefits of implementing V2G/V2B strategies to account for seasonal fluctuations and long-term trends in the electricity market, and to capture the integration of renewables. For example, over several months or a year.

### 1.3. Contributions and novelty of this research

The goal of this paper is to address the identified research gaps and to quantify the potential of a V2G framework in a manufacturing company. It focuses on using employees' EVs as temporarily battery storage for price-based DR and self-consumption optimization and assessing its impact on the company and on EV batteries. To achieve this, we apply a MILP model for multi-objective optimization (MOO) targeting the company's energy costs and the battery degradation of EVs on real-world data from a German company for different scenarios and contexts. This load model was based on empirical data from a manufacturing factory in Germany. The recorded grid and climatic data were obtained from corresponding times and locations as the load, along with consideration of the peak price of the electricity grid (EG) and the maximum import capacity (MIC) of the company, established a reality-based approach. The modified EV battery degradation model is based on an existing model [9], which was validated using empirical data.

We simulate a smart grid to study DR based on the German RTP electricity price for the year 2022, using empirically derived parameters such as load efficiencies and charging rates. The case study examines a smart grid with a V2G-enabled EV fleet, considering factors such as EV availability, 15 min resolution electricity prices, weather data, and a battery degradation model. A key objective is to minimize cycle degradation, taking into account battery temperature, C-rate, and the average SOC of each EV on site at the company. Within this framework, the benefits for EV owners should be at least as high as the costs of battery degradation, if not many times higher, to achieve general acceptance of V2G.

Therefore, the paper addresses the aforementioned gaps in the current research field and the novelty of the paper can be presented as follows:

(i) The development of a MILP model to operationally optimize a charging strategy that minimizes corporate energy costs through price-based DR and self-consumption optimization while minimizing battery degradation for EV owners during charging and discharging of their EV battery.
(ii) Analysis of the company's energy costs and an assessment of the potential battery degradation through DR, while showing a mutually beneficial trade-off for both stakeholders (company and EV owners).
(iii) The comparison of the impact of AC and DC charging on economic profitability for EV owners and the company in the context of V2G.
(iv) In this novel approach, we investigate the interaction of C-rate and battery capacity of EVs and evaluate their impact on V2G optimization.

The remainder of this paper is organized as follows: An overview of the system is given in Section 2. Then, the optimization model is described in Section 3 and the case study data in Section 4. Subsequently, the scenarios for analysis are defined in Section 5, before the results are elaborated and discussed in Section 6. Finally, Section 7 provides concise conclusions.

## 2. System description

### 2.1. Overview

In this paper, we propose a decentralized optimization framework for planning the charging and discharging of EVs. The focus of this research is on implementing an optimization framework that has impacted energy distribution by fostering collaboration among different stakeholders. In our decentralized approach, it is the manufacturing company with a high and variable electricity demand typical for production, and the company's employees, who provide and are compensated for providing their EVs for V2G purposes. Our focus is on maximizing stakeholder benefits, through SC, V2X, and smart grid services such as energy arbitrage, DR, and self-consumption optimization. These services are designed to benefit stakeholders, at multiple levels, from transmission to behind-the-meter services such as peak load reduction, energy bill reduction, and potential emissions reduction. The framework of this study is presented in Fig. 1.

### 2.2. Assumptions for the mathematical model

The modeling of the V2G framework is dependent on a variety of parameters, including EV battery specifications, technical constraints, company capabilities, EV availability, MIC, battery capacity, battery chemistry, and practical procedures. In this paper, the following assumptions are made for the simulation of the optimization model, which have been adopted and extended from [48]. These assumptions are valid for all cases and scenarios:

- All time series are provided in quarter-hourly resolution.
- The time span in which V2G services can take place in the company is from the arrival time to the departure time. Each charging or discharging operation takes at least 15 min.
- The battery temperature is determined by calculating the moving average of the ambient temperature. This ambient temperature is measured every hour on the company premises and the moving average is based on the last three hours.
- The historical price signals of the German electricity spot market in 2022 were used for optimization. Moreover, the purchase price for electricity is higher than the sale price in each time step as it includes taxes and levies, and purchase and sale prices are not changed by charging or discharging EVs.
- The effect of charging on battery degradation is the same as that of discharging, which is in line with the results of Saxena et al. [49].
- Degradation that occurs outside the company's availability window and the impact of calendar-based degradation do not influence the optimization process. The company is equipped with the necessary charging infrastructure for the proposed concept, and the limits of grid import and export are not exceeded.
- The load profiles of the company's electricity demand are known.
- EV battery SOC, arrival and departure time, and final SOC at departure time are known.
- The maximum EV charging C-rate will not change during V2G service up to a SOC of 80%. Above 80%, the C-rate decreases to 50% of the maximum charging rate.
- Any energy exchange or energy consumption of the EVs by driving or charging beyond the time limits where the EV is available to the company is not considered.
- EV batteries are considered to have reached the end of their life (EOL) when their state of health decreases to 80%.

## 3. Optimization model

### 3.1. Framework

The input parameters of the EV planning model were selected based on technical constraints, the theoretical capabilities of the company and practical methods. To investigate the trade-off between the company and the EV owner, we developed a deterministic MILP model. The Demand Response Analysis Framework (DRAF), an open-source Python tool developed for the environmental and economic analysis of DR, was used as the underlying simulation environment for this purpose [50]. The Gurobi 9.5 solver was used to solve the model through its Python interface [51]. All the simulations have been carried out on a virtual machine, with an Intel® Xeon® Processor E5-2670 v3 CPU 2.3 GHz processor with 12 cores and 64 GB RAM. Throughout the analysis, we assume perfect foresight and simulate a year with 15 min time steps $t \in T$, i.e. 35,040 time steps and $\Delta t$ = 15 min. The use of 15 min time steps in the EV fleet planning model is quite beneficial, especially considering that the spot markets also operate in the same 15 min intervals. This synchronization allows for a more accurate representation of market dynamics and thus a better match between the simulations and actual market conditions.

### 3.2. Objective function

To realize the multi-objective planning strategy for the DR, the minimization of the total company's cost (TCC) is combined with the minimization of the battery degradation costs (BDC) of the EVs based on the real-time electricity price in the electricity market. The blended objective function of the MILP problem to be minimized is given by (1).

$$C^{\mathrm{TOT}}_{\mathrm{argmin}} = (1-\alpha)\,\mathrm{TCC}^{\varphi} + \alpha \mathrm{BDC}^{\varphi} \tag{1}$$

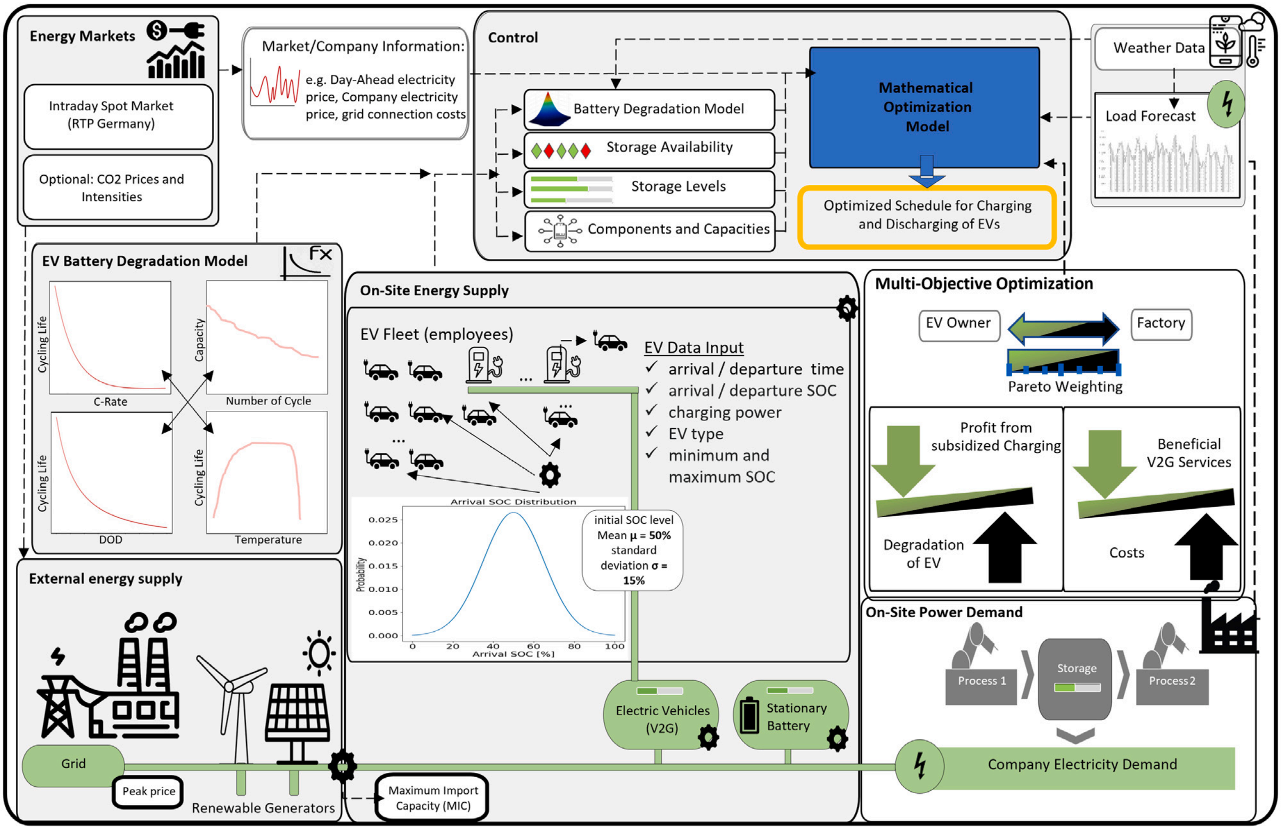


**Fig. 1.** Overview diagram of the MILP model. It shows the external energy supply (bottom left), the on-site energy supply (middle) including the EV fleet, the associated charging infrastructure, the energy demand of the company (bottom right) and the energy flows between these components. The energy market is shown at the top left and the battery degradation model is shown below. The controller (optimization model) collects all available information (battery degradation model, market data, storage availabilities and levels, weather data, and smart grid energy components) and creates an optimized schedule for charging and discharging EVs based on the parameters of the MOO's objective function (center right).

where $C^{\mathrm{TOT}}_{\mathrm{argmin}}$ are the total costs to be minimized (TCC and BDC). The values of the TCC in €/year and the cost of degradation in €/year are scaled by a normalization factor $\varphi$ to have the same order of magnitude. The Pareto weighting factor $\alpha$ is varied between 0 and 1 to produce Pareto-optimal planning strategies and to analyze the optimal trade-off between profit for the company and battery degradation of the EVs.

### 3.3. Total company costs

$$\mathrm{TCC} = \sum_{t=1}^{N} \left( P_t^{\mathrm{dem}} + P_{t,i}^{\mathrm{EV,ch}} - P_{t,i}^{\mathrm{EV,dis}} \right) \Delta t \pi_t + C^{\mathrm{EG,NF}} \tag{2}$$

where $P_t^{\mathrm{dem}}$ is the electricity demand at time t, $P_{t,i}^{\mathrm{EV,ch}}$ is the power supplied to the EVs at time $t$, and $P_{t,i}^{\mathrm{EV,dis}}$ is the power discharged from the EVs at time $t$. $\pi_t$ is the RTP at time $t$, which is assumed to be a known parameter for optimization. $N$ is the total number of time steps, and $\Delta t$ is the time step. $C^{\mathrm{EG,NF}}$ are network fees for purchased electricity from the EG, which is defined by:

$$C^{\mathrm{EG,NF}} = P_{peak}^{\mathrm{EG,buy}} c_{peak}^{\mathrm{EG,buy}} \tag{3}$$

where $P_{peak}^{\mathrm{EG,buy}}$ is the annual peak power transmitted from the EG, $c_{peak}^{\mathrm{EG,buy}}$ is the peak price. The buying price is higher than the selling price from the EG because taxes and levies are added to the electricity purchase. Therefore, the price signal $\pi_t$ must be adjusted so that:

$$\pi_t = \begin{cases} P_t^{\mathrm{EG,consumpt}} (c_t^{\mathrm{RTP}} + c^{\mathrm{EG,addon}}), & \text{if } P_t^{\mathrm{EG,consumpt}} \geq 0, \\ P_t^{\mathrm{EG,consumpt}} c_t^{\mathrm{RTP}}, & \text{otherwise.} \end{cases} \quad \forall t \tag{4}$$

The sum of the total electricity consumption is represented by $P_t^{\mathrm{EG,consumpt}}$. If this value is positive, electricity is drawn from the grid. If it is negative, electricity is sold. When electricity is drawn, the time-independent fixed energy price $c^{\mathrm{EG,addon}}$ is added to the dynamic RTP costs $c_t^{\mathrm{RTP}}$. Since there is a MIC, the electricity purchased and sold from/to the EG is not allowed to exceed it. $P^{\mathrm{EG,MIC}}$ ensures that the consumption (positive and negative) does not exceed the maximum installed capacity.

$$|\mathrm{P}_t^{\mathrm{EG,consumpt}}| \leq \mathrm{P}^{\mathrm{EG,MIC}}, \quad \forall t \tag{5}$$

### 3.4. Battery degradation cost (BDC)

The model used in this paper to calculate battery degradation, focuses only on cyclic degradation, as it is directly influenced by the operation of the battery and thus directly influenced by additional charge and discharge cycles in the optimized charging schedule. For that reason we exclusively focus on the main factors that cause and/or intensify battery cyclic degradation, such as battery temperature, C-rate, SOC and DOD [47,52]. Therefore, we use the battery degradation model from [9], which is developed empirically from laboratory experiments. This model was adopted because, firstly, it takes into account battery temperature, C-rate and SOC and it enables the assignment of a monetary value to cyclic degradation. Secondly, this dynamic model is based on commercially available lithium-ion cells for EVs and allows for the estimation of battery degradation at each time step per kWh exchanged.

However, a limitation of this model is that the battery temperature is assumed to be based on the average daily ambient temperature. To address this limitation, we propose a modification to the model where we calculate the battery temperature as a moving average of the actual measured ambient temperature at each specific time step. This change not only accounts for the fluctuations in air temperature throughout the day, but also effectively smooths out any transient temperature spikes. The result is a more accurate representation of the real-time ambient temperature in the immediate vicinity of the battery (housed within the EV), which increases the practicality of the model. In this modified model, the degradation cost of the battery during each time step of V2G utilization, is calculated as follows:

$$BDC = \sum_{t=1}^{N} \left( C_{t,i}^{\text{deg}} E_{t,i}^{\text{exch}} \right) \Delta t, \quad \forall t, i \tag{6}$$

where $C_{t,i}^{\text{deg}}$ is equal to the battery degradation cost per time step incurred by exchanging 1 kWh, $E_{t,i}^{exch}$ is the net amount of electricity exchanged (in kWh) by the $i$th EV at time $t$. The cost of degradation is calculated at each time step. All equations refer to the time period in which each individual EV is available. This is ensured by using a Boolean variable indicating the availability of each EV. The calculation of the degradation of the battery of each EV at time $t$ is given in the model as follows:

$$C_{t,i}^{\text{deg}} = C^{\text{Bat}} \left( \frac{0.2}{2\ (\alpha_{t,i}^{c}) E_i^{\text{EV,cap}} \text{DOD}} \right)^{-1} \quad \forall t, i \tag{7}$$

where the numerator $C^{\text{Bat}}$ represents the capital cost of the battery in €/kWh. Since capital costs are crucial for the evaluation of battery degradation costs, we have adopted battery costs that are compatible with prices from an analysis of industry technical reports and announcements from [53]. The denominator provides the calculated energy throughput in kWh under certain charging and discharging conditions at time step $t$ before the battery reaches EOL. $\alpha_{t,i}^{c}$ represents the battery degradation coefficient at every time step $t$ and for every EV, and $E^{\text{EV,cap}}$ is the maximum EV battery capacity of each EV. Since a cycle is defined as a complete sequence of charging and discharging, we use a coefficient of 2 in Eq. (7). The battery degradation coefficient $\alpha_{t,i}^{c}$ affected by the external stress factors can be defined accordingly as (adopted from [9]):

$$\begin{aligned} \alpha_{t,i}^{c} \left( T^{\text{Bat}}, P_{t,i}^{\text{EV,ch}}, P_{t,i}^{\text{EV,dis}} \right) = {} & \left[ \beta_1 (T^{\text{Bat}})^3 + \beta_2 (T^{\text{Bat}})^2 + \beta_3 T^{\text{Bat}} + \right. \\ & \left. \beta_4 \right] \left[ \beta_5 CR_i^{\text{EV}} + \beta_6 \right] \left[ \beta_7\ \bar{E}_i^{\text{EV}} + \beta_8 \right] \end{aligned} \tag{8}$$

In (8), $T^{\text{Bat}}$ represents the battery temperature of the EV, $CR^{\text{EV}}$ is the C-rate of the EV charger, $\bar{E}_i^{\text{EV}}$ is the average SOC of the $i$th EV during battery utilization, and $\beta_{1\to 8}$ are fitting parameters. The fitting parameters for the battery degradation model used in this work are taken from [54]. In our approach, the average SOC during battery operation is considered an external constraint, i.e., it influences the optimization, but its impact cannot be minimized. Quantifying the battery degradation cost incurred during each charging or discharging operation, at each time step, allows the algorithm to determine whether the EV should be charged or discharged. This depends on both the Pareto weighting factor of the objective function and the amount of charging or discharging involved. In this way, all costs and losses incurred during charging or discharging (including degradation costs and efficiency losses) are balanced with the benefits of taking advantage of fluctuating electricity prices and electricity demand of the company. This enables the simulation of an optimal charging strategy for each EV, based on the assigned Pareto weighting factor.

### 3.5. Electric vehicle (EV) modeling

EVs are modeled as multiple energy storage systems similar to battery energy storage (BES), but with limited availability and variability in arrival and departure SOC at the company's workplace. These are based on technical limitations and practical considerations. The SOC of each EVs is tracked exclusively during the time of presence at the workplace (if the EV is not at the workplace, the SOC equals to 0). In addition, the EVs differ to BES in terms of C-rate, battery degradation variables and SOC limitations. The bidirectional power flow for V2G of the EVs is provided from the time of arrival until the departure time of the working day. The EV constraints are (9)–(15):

$$E_{t,i}^{\text{EV}} = \begin{cases} E_{t,i}^{\text{EV,arr}}, & \text{if } t = t_{\text{arr}} \\ \left(1 - \eta_{\text{self}} \Delta t\right) E_{t-1,i}^{\text{EV}} + \Delta t \left( \eta_i P_{t,i}^{\text{EV,ch}} - \frac{P_{t,i}^{\text{EV,dis}}}{\eta_i} \right), \\ \text{otherwise} \end{cases} \tag{9}$$

$$P_{t,i}^{\text{EV,ch}} \le \text{CR}_i^{\text{EV,ch}} E_i^{\text{EV,cap}} y_{t,i}^{\text{EV,ch}}, \quad \forall t, i \tag{10}$$

$$P_{t,i}^{\text{EV,dis}} \le \text{CR}_i^{\text{EV,dis}} E_i^{\text{EV,cap}} y_{t,i}^{\text{EV,dis}}, \quad \forall t, i \tag{11}$$

$$E_{t,i}^{\text{EV}} = E_i^{\text{EV,dep}}, \quad \text{if } t = t^{\text{dep}} \tag{12}$$

$$\lambda^{\min} E_i^{\text{EV,cap}} \le E_{t,i}^{\text{EV}} \le \lambda^{\max} E_i^{\text{EV,cap}}, \quad \forall t, i \text{ if } y_{t,i}^{\text{EV,avail}} = 1 \tag{13}$$

$$y_{t,i}^{\text{EV,ch}} + y_{t,i}^{\text{EV,dis}} \le 1, \quad \forall t, i \tag{14}$$

$$\text{CR}_i^{\text{EV,ch}} = \begin{cases} 0.5\ \text{CR}_i^{\text{EV,ch}}, & \text{if } E_{t,i}^{\text{EV}} \ge 0.8 \\ \text{CR}_i^{\text{EV,ch}}, & \text{otherwise} \end{cases} \tag{15}$$

Eq. (9) represents the stored energy of the EVs. When the EV arrives at the workplace, the energy stored in the battery is measured by $E_{t,i}^{\text{EV,arr}}$. Then the stored energy can be altered by adding the charged energy and subtracting the discharged energy, considering the efficiency of the charger $\eta_i = 0.95$ [30]. $E_i^{\text{EV,cap}}$ represents the maximum usable battery capacity of the EV. The constraints (10) and (11) limit the charging and discharging power of the EVs, respectively. Eq. (12) defines the required energy that the EVs need to have at their departure time. To avoid a higher degradation of the EV batteries and to allow a minimum range for unforeseen trips, the capacity limits are set in (13).

The limitation of the minimum SOC was set at 0.2 to provide EV owners with confidence that their EV would retain enough charge for short trips during their shift. The study by Ghotge et al. [55] identified that good communication regarding the impact of V2G on batteries, financial compensation and real-time insight into SOC encouraged EV owners to participate in V2G. Furthermore, a survey of 749 participants in Germany revealed that EV owners are generally willing to participate in V2G, provided that financial compensation is offered to offset any resulting disadvantages [56]. Heuveln et al. [57] also demonstrated that the majority of EV owners accepted V2G on the condition of financial compensation. Eq. (14) ensures that charging and discharging do not occur simultaneously.

In Eq. (15), the C-rate of the EVs is modified so that the C-rate for the respective EV is reduced to 50% of its regular value when the SOC of the EV is equal to or greater than 80%. Given the empirical evidence and the detailed analysis of [58], it is recommended to charge EVs within the SOC of 20% to 80% to optimize energy efficiency and to extend battery life. However, to allow a slightly wider scope for DR, we assume a range of $\lambda^{\min} = 0.2$ and $\lambda^{\max} = 0.9$.

## 4. Input data

The technology and model parameters of this study are listed in Table 2.

**Table 2**
Technology and model parameters.

| Parameter | Value |
|---|---|
| Number of EVs | 10 |
| Battery Arrival SOC | $\mu = 0.5$, $\sigma = 0.15$ |
| Battery Departure SOC | Arrival SOC + $\Delta$ SOC (0, 5, 10, 15, 20, 25, 30%) |
| V2G window | 6:00 a.m.–4:00 p.m. (Mon–Fri) |
| Efficiency EV charger $\eta$ | 0.95 |
| Self-discharge $\eta^{self}$ | 0.002%/h [59] |
| Time resolution $\Delta t$ | 15 min |
| Simulation Period | 1 year |
| EOL battery | At 80% |
| Battery Cost (€/kWh) | 150 |
| Pricing strategy | RTP Germany |
| Electric load | Industry (manufacturing) |
| Peak load without EVs | 400 kW |
| Peak-to-average ratio | 1.48 |
| Maximum import capacity (MIC) | 140% of peak load |

### 4.1. Electricity grid prices

We consider the electricity purchase costs under the RTP tariff, a prevalent offering by numerous electricity suppliers in today's market. The tariff comprises three main components: a time-based energy price denoted as $c_t^{\mathrm{RTP}}$, a fixed price component $c^{\mathrm{EG,addon}}$, and a power price component represented as $c_{\mathrm{peak}}^{\mathrm{EG,buy}}$ as illustrated in Eq. (3). For $c_t^{\mathrm{RTP}}$, we assume historical 15 min electricity prices of the year 2022, as shown in Fig. A.1 (respectively Fig. A.2). The data were obtained from the ENTSO-E transparency platform [60] using the Python package elmada [61]. It was assumed there was a surcharge of $c^{\mathrm{EG,addon}}$ of €42.57/MWh, which included €27.19/MWh for taxes and levies [62] and €15.38/MWh sale costs adopted from [63]. In addition, the company was obliged to pay a power price $c_{\mathrm{peak}}^{\mathrm{EG,buy}}$ of €70/kW for the power drawn from the energy supplier.

### 4.2. Electric vehicle owner

For modeling the behavior of EV owners, the arrival and departure time and the arrival SOC and departure SOC are crucial. In this study, we assume a scenario in which employees travel to the company daily on weekdays (Monday to Friday) and leave after a fixed 10-hour shift. This assumption is based on the company's operational structure, which runs exclusively on weekdays and applies the shift models commonly used in the manufacturing industry. Given the manufacturing nature of the company, employees adhere to a strict clock-in, clock-out system, clocking in at 6:00 a.m. and clocking out at 4:00 p.m. Accordingly, the arrival times of the employees are tightly clustered around the start of their shift, rendering a statistical distribution unnecessary in this context.

For the EVs' initial SOC upon arrival, we assume a normal distribution. This approach is consistent with existing V2G research practices [64]. In this study, the SOC of the EVs is assigned randomly for each working day with a truncated normal probability distribution (mean SOC $\mu = 0.5$, standard deviation $\sigma = 0.15$). This truncation prevents the selection of values greater or equal to $3\sigma$, ensuring realistic SOC limits. The departure SOC of the EVs is increased to the arrival SOC as the starting point by the amount of free charge received. This amount of free charging is referred to as $\Delta$ SOC in this paper from here on in. Therefore, $\Delta$ SOC 10% indicates that the EV owner receives a share equal to 10% of the capacity of their battery. For example, if the battery has a capacity of 100 kWh, the owner is entitled to 10 kWh of free electricity in return for making their battery available to the company for a single workday.

### 4.3. EV type

The technical restrictions of the EVs (battery capacity and C-rate) are decisive for the optimization. Table 3 provides an overview of the electrical characteristics of the EVs utilized in the simulation. For the simulation, 10 different EVs were assumed (each EV type selected once from Table 3) to make comparisons among EVs regarding the impact of battery capacity and C-rate on battery degradation and the benefits to the company from V2G. These EVs are either currently undergoing testing in pilot projects or have the capability to adopt V2G technology in the future [65]. To ensure a thorough investigation, we have included EVs with small, medium and large battery sizes and C-rates in our simulations.

### 4.4. Company load profile

For the analyses, we used the historically measured electricity demand of the manufacturing company from southern Germany, which was available to us in 15 min resolution (see in heatmap Fig. A.3). Since each EV is simulated over the entire period of one year, we consider 10 EVs to keep the calculation time within a feasible range. To simulate the impact of the 10 EVs in a smaller company setting, the load profile was scaled down from an initial peak demand of 6840 kW to 400 kW. This modification resulted in a reduction of the annual electricity consumption from 36 GWh/yr to 2.10 GWh/yr, reflecting the scenario of a company with 10 EVs in its parking lot. Accordingly, the MIC was also scaled down to the same extent. The average weekly profile with a 95% confidence interval post-scaling is shown in Fig. A.4.

### 4.5. Weather data

For the battery degradation model, weather data were used based on historical dry bulb air temperature data from the nearest weather station to the company, as provided by German Weather Service. For reasons of anonymity, the geographical coordinates are not given. The measured temperature used for the simulation is shown in Fig. A.5.

## 5. Scenario setting

We modeled three cases: A non-optimized reference case (REF), an optimized SC case (1), and an optimized V2G case (2). The case definition, with the different characteristics, is summarized in Table 4. To evaluate the potential benefits of the proposed method, V2G is not considered in the first two cases. In the REF case, a reference scenario is simulated to find the net electricity costs of the company without any EVs. This scenario represents the non-optimized status quo. The electricity demand is only covered by the EG. In Case 1, SC of EVs is simulated. The EVs can only be charged. The arrival and departure times, as well as the SOCs of the EVs are the same for all scenarios to create comparability (the seed function is used). Case 1 is used as a benchmark to study the impact of V2G on the company's profitability.

The battery degradation costs are calculated as shown in Section 3.4, except that there is no discharging of the EVs. In Case 2, the EVs are not considered as a load that needs to be charged, instead they are used as energy storage. Case 2 examines the costs of the company and the costs due to battery degradation. In this course, different levels of free charging to the EV owners will be investigated (these are also simulated in Case 1 for comparability). Moreover, an additional analytical consideration involves the analysis of the comparability of the different EVs in terms of profit per EV depending on net capacity and C-rate for the company and for the EV owners, as well as the different levels of battery degradation.

**Table 3**
Electrical characteristics of EVs used for the simulation. For DC charging, the calculated average charging speeds from [66] were adopted, since assuming the maximum DC charging speed is not feasible.

| EV type | Net battery capacity [kWh] | AC charging power [kW] | Average DC charging power [kW] | C-rate (AC/DC) |
|---|---|---|---|---|
| Audi Q4 e-tron | 76.6 | 11 | 103 | 0.14/1.34 |
| Citroën C-Zero | 14.5 | 3.7 | 30 | 0.26/2.06 |
| Ford F-150 lightning | 125 | 19.2 | 127.8 | 0.15/1.02 |
| Honda e | 28.5 | 6.6 | 32 | 0.23/1.12 |
| Kia EV6 | 74 | 11 | 200 | 0.15/2.70 |
| Mercedes 350 EQE | 89 | 22 | 120 | 0.25/1.35 |
| Mitsubishi outlander (PHEV) | 12 | 2.3 | 30 | 0.19/2.50 |
| Nissan leaf e+ | 59 | 6.6 | 44 | 0.11/0.75 |
| Volvo EX90 | 107 | 11 | 150 | 0.10/1.40 |
| VW ID 5 | 77 | 11 | 103 | 0.14/1.34 |

**Table 4**
Simulation case studies.

| Case | EV fleet | DR | V2G | Battery degradation |
|---|---|---|---|---|
| REF | – | – | – | – |
| Case 1 | ✓ | ✓ | – | ✓ |
| Case 2 | ✓ | ✓ | ✓ | ✓ |

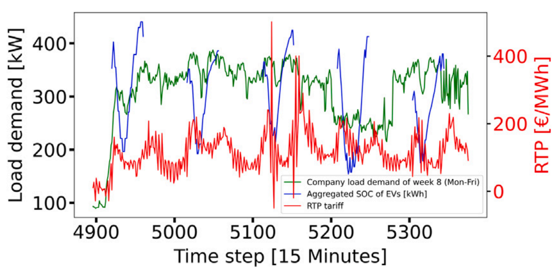


**Fig. 2.** Illustration of the aggregated SOC changes of the EVs when V2G is enabled. Pareto value of 0.5, AC charging, and $\Delta$ SOC 10%.

## 6. Results and discussion

In the following section, the results of each case study are described individually and discussed in the summary section. First, a temporal analysis was performed to identify the week with the most representative variance in the company's load profile among the 52 weeks of the evaluation period. This week was then selected to illustrate the optimization strategies for V2G-cases. Using this specific week, Fig. 2 shows the aggregated SOC for all 10 EVs (blue line) and illustrates how the SOC changes as a function of the objective function. During the availability periods of the EVs, the optimization algorithm manipulates the charging/discharging of the batteries in the EVs, also depending on the battery degradation model applied (if the EVs are not available, the SOC is 0).

### 6.1. Reference case (REF) and smart charging (Case 1)

An overview of the economic and energy impacts stemming from the REF Case and Case 1 are presented in Table A.1. It highlights important factors such as total electrical costs for the company and aggregate degradation costs of EVs. "AC" and "DC" indicate the type of current used for charging and discharging EVs, $\Delta$ SOC denotes the percentage of free charging of EVs. It can be seen, as expected, that the total annual costs increased in all scenarios of Case 1 compared to the REF case without EVs, since the EVs are only charged and not discharged. This cost increase is observed for both AC and DC charging. Noticeably, degradation costs do not exist in the REF Case, but increase with higher $\Delta$ SOC in the Case 1 scenarios. Interestingly, degradation costs are generally higher for DC charging than for AC. At the same SOC level, the degradation costs of DC are 75.28%, 71.53%, 70.44%, and 65.66% higher than AC charging, respectively, with the rate of change decreasing slightly as the $\Delta$ SOC level increases. This effect is caused by the higher SOC required on departure, which limits the previous optimization capabilities after arrival until departure.

### 6.2. V2G scenarios (case 2)

In both Case 1 and Case 2, the peak load on the grid remains unchanged compared to the REF scenario. As a result, the MIC is not exceeded. This illustrates that despite an increased total load due to EVs, an increase in peak load can be prevented by an intelligent energy system. Considering that the focus of this work is to analyze V2G in a non-residential DR scenario, the multi-objective optimization used a Pareto analysis to investigate the optimal trade-off between company profit and battery degradation.

#### 6.2.1. Pareto analysis

The company's profit from V2G is the profit for the company derived from utilizing the EVs' batteries compared to the REF Case without EVs. Based on degradation, the company's profit from V2G and the profit of the 10 EV owners for the simulated period are compared for 11 values of $\alpha$, 0 to 1 in increments of 0.1. To calculate the combined net profit of EV owners, a home tariff of €0.39/kWh was used as the reference price for each kWh provided to the EVs, creating a uniform basis for the profit calculation. The standard home tariff in Germany ranged between €0.37 to 0.40/kWh according to [62] in 2022. The Pareto front of the analysis is shown in Fig. 3 as a function of profit for the company and maximum degradation (blue) and from the perspective of aggregate profit for EV owners (red). The sum of these two profits (green) represents the most beneficial economic outcome, i.e., the sum of the net profit for the EV owners and the profit for the company from V2G. In the case where $\alpha = 0$, every opportunity to reduce the company's energy costs is fully exploited. In contrast, when $\alpha$ is set to 1, the EVs are charged in an optimized manner that minimizes battery degradation from the arrival SOC to the departure SOC level, i.e., when the degradation per charged kWh is lowest. Thus, the EVs are charged as a function of optimal temperature.

This means that V2G does not occur, as EVs will not perform any discharge activities. The results indicate that as the Pareto weighting is shifted further towards cost minimization for the company, there is a noticeable increase in battery usage and, consequently, a higher degree of degradation of the EV batteries (decreasing $\alpha$-value). This leads to a reduction in the net profit for the EV owners due to the increased degradation costs. In the AC charging scenario, a profit for the company is not realized until the $\alpha$-value approaches 0.6 (at approximately 0.58), while in the DC charging scenario, a profit is realized at an $\alpha$-value of 0.7. Interestingly, the net profit for EV owners varies more with DC

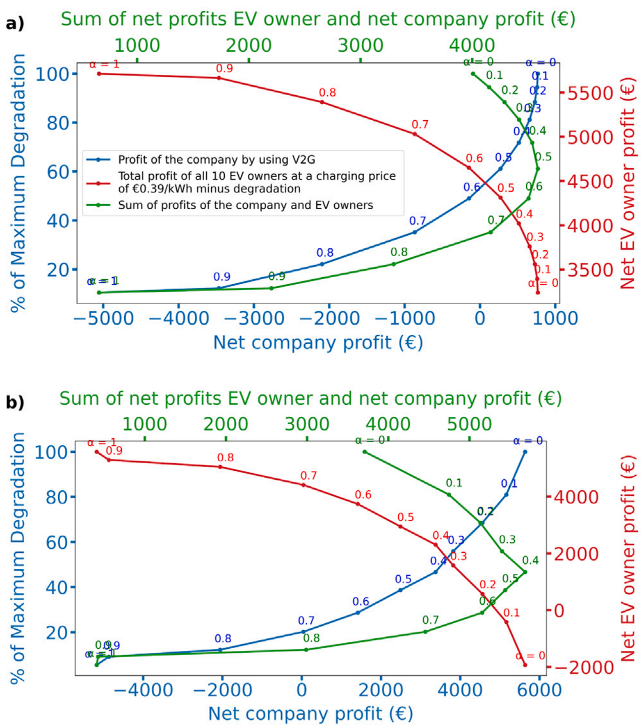


**Fig. 3.** Pareto analysis for the optimized scheduling model for the 10 EVs for AC charging (a) and DC charging (b) at an 8% $\Delta$ SOC level with $\alpha = 0$ minimizing energy cost, $\alpha = 1$ minimizing degradation.

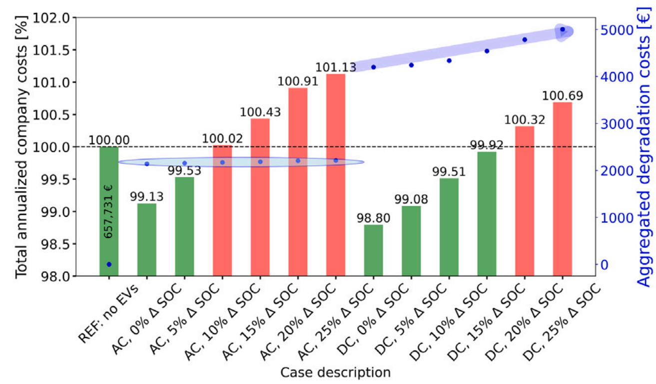


**Fig. 4.** Sensitivity analysis of the company's annualized costs with respect to different levels of $\Delta$ SOC for AC and DC charging and for the REF Case.

charging (−€2000 to €5581), while it has a smaller range with AC charging (€3240 to €5714). This indicates a differential sensitivity of profitability with respect to the chosen charging method. The optimal profitability, found at an $\alpha$-value of 0.4 in the DC charging scenario, is a value of €5683 and at a $\alpha$-value of 0.5 in the AC charging scenario (€4586).

Finally, it can be concluded that both the company and the EV owners can benefit from this concept, even if the company provides free charging to the EV owners.

### *6.2.2. Sensitivity analysis*

The results of the simulations reveal some important observations and analytical insights about the sensitivity of the company's total annual cost to different $\Delta$ SOCs provided to the EV owners for both AC and DC charging scenarios, as seen in Fig. 4. The observed results indicate that there is a specific threshold for changes in $\Delta$ SOC. When this threshold is exceeded, the company's annual cost surpasses the company's annual cost in the REF Case. For the AC charging system, the company's annualized cost exceeds the REF cost (€657,731) when the $\Delta$ SOC reaches 10%. The company's annualized cost at this point is €657,892, slightly higher than in the REF Case. For the DC charging system, this threshold is at 20% $\Delta$ SOC, where the company's annualized cost is €659,811. Furthermore, it is evident that for different $\Delta$ SOC values, the company's total annualized costs for DC charging scenarios are consistently lower than those for AC scenarios, with costs between 0.33% and 0.59% (€2173 to €3910) lower for DC scenarios.

The discrepancy in $\Delta$ SOC thresholds between the AC and DC charging systems can be attributed to the DC system's ability to charge and discharge at high C-rates, enabling more rapid and responsive utilization of EV battery capacity. This allows the company to exploit real-time electricity prices more effectively and achieve a higher threshold $\Delta$ SOC for the DC system as compared to the AC system. In terms of degradation costs, it appears that the proportion of degradation costs for the EV owners relative to the company's annual costs is higher in DC charging scenarios compared to AC charging scenarios. Specifically, the ratio of degradation costs to total annual costs in AC charging scenarios remains relatively stable, increasing by approximately 3.17% as the $\Delta$ SOC increases from 0% to 25%. In contrast, the DC charging scenarios show a more pronounced increase in this percentage, increasing by approximately 13.95% as the $\Delta$ SOC increases from 0% to 25%. The degradation costs in the DC scenarios are consistently higher than in the AC scenarios, with differences to AC costs ranging from €2058 to €2796, an increase of 96% to 127%.

Fig. 5 shows the profit dynamics for both the company and the EV owners at different $\Delta$ SOC in two different charging scenarios, AC and DC charging with a benchmark price if EV owners had charged their EV at home at a price of €0.39/kWh. Battery degradation costs are already factored into the EV owners' profit. Fig. 5 illustrates the transition points of profitability for both parties, with the company initially making high profits at lower $\Delta$ SOC values that turn into losses as the $\Delta$ SOC increases. Conversely, the EV owners will transition from losses to profits. For AC charging, a profit transition for the EV owners occurs between 2.5% and 5% $\Delta$ SOC. For DC charging, a profit transition for the EV owners occurs between 5% and 7.5% $\Delta$ SOC due to higher battery degradation costs.

In general, DC charging brings the company a higher profit compared to AC charging even if the $\Delta$ SOC increases. The green highlighted zone characterizes the sector where both stakeholders benefit. In the orange areas, only one stakeholder benefits, and in the red area, none. There is a clear linear inverse relationship, as the profit for the company decreases with increasing $\Delta$ SOC, the profit for the EV owners increases. Finally, Fig. 5 shows that DC charging is more beneficial to the company, while AC charging is more beneficial to EV owners. In the case of AC charging, it is noticeable that this method cannot fully utilize the high battery capacities of some EVs due to the relatively low C-rate. EV owners benefit more from this scenario due to the lower rate of degradation incurred. Conversely, the advantages of DC charging for the company are that the EV batteries can be better utilized due to the higher C-rate. With DC charging, EV owners incur higher costs for battery degradation and this results in a lower profit for EV owners.

### *6.3. EV characteristic analysis*

Fig. 6 shows the results of the EV profit comparison over one year for both AC (top) and DC charging (bottom) scenarios for the company and EV owners (including degradation). The V2G scenarios are divided into five different cases each, providing free $\Delta$ SOC to the EVs from 0% to 20% (in 5% increments).

The AC charging scenarios show a significant decrease in the company's profitability for all EV models as the percentage of $\Delta$ SOC increases. In general, the transition from profitability to unprofitability in a V2G environment varies significantly across EV models. The

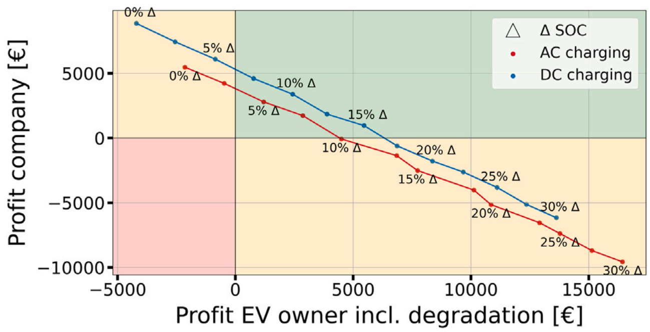


**Fig. 5.** Trade-off between the company and the aggregated profits of the EV owners over different Δ SOC under two charging scenarios — AC and DC. A benchmark price of €0.39/kWh is assumed for charging EVs at home.

majority of the EVs studied enter the loss zone (from the point of view of the company) at 10% to 15% Δ SOC (and between 15% and 20% for DC scenarios).

In this context, two factors play a crucial role. First, the company has to provide more free electricity for larger batteries, which leads to lower profitability for the company. In addition, the difference between AC and DC charging systems is striking. AC charging cannot fully utilize the high battery capacities of some EVs, such as the Volvo, which has a 107 kWh battery but only a limited AC charging capacity of 11 kW, constraining the company's ability to fully exploit the battery for DR purposes and allowing EV owners to benefit more from a higher Δ SOC. DC charging, on the other hand, allows the company to better utilize these large battery capacities in a working day, as the C-rate is increased substantially.

Furthermore, increasing Δ SOC brings additional constraints on the optimization process, as higher departure SOCs result in a shorter time window for implementing DSM strategies. These constraints inevitably reduce the profitability of the company, which underscores the importance of addressing this dynamic. As a result, EVs with smaller batteries tend to be more resilient to degradation in AC scenarios than in DC scenarios, as the limited C-rate prevents the batteries from being fully utilized. Larger batteries receive more free charging, resulting in lower profitability for the company, while the limited C-rate has a lower economic impact on the smaller batteries than on the larger ones, reducing the extent of degradation compared to the larger batteries. In fact, all EV owners in AC scenarios make a profit at a Δ SOC level of 5% and in DC scenarios at a Δ SOC level of 10% despite battery degradation (see Fig. A.6).

The economics of AC charging show a recognizable pattern where EV owners realize significant benefits from increased battery capacity. The positive correlation between battery size and profit is evident, demonstrating that larger battery capacity leads to higher financial gains for EV owners. This effect is attributed to the reduced impact of low C-rate on battery degradation. The Kia EV6, which has the highest DC C-rate at 2.70, transitions quite dramatically into unprofitability. The Mitsubishi Outlander shows the same effect, with a high DC C-rate of 2.5, but a modest net battery capacity of 12 kWh, demonstrating that a high C-rate does not exempt a vehicle from profitability risks, even if the battery capacity is low.

In addition, the results highlight the limitations associated with EVs with smaller batteries, such as models like the Citroen C Zero and Mitsubishi Outlander. These EVs face a double challenge. Firstly, their limited battery capacities limit the company's profit potential, as the low level of energy storage does not allow for significant economic profits. Secondly, owners of such vehicles endure a significant impact from high degradation, especially in DC charging scenarios. Fig. 7 shows a comparative boxplot analysis of the distribution of full cycles on the company site for each of the 10 different EV models in the simulated year, considering variations in the Δ SOC in both AC and DC charging scenarios. Thus, DC charging reveals a remarkable finding which suggests that a significantly increased C-rate can also be profitable for EV owners. This peculiarity arises from the ability of a higher C-rate to reduce the number of cycles, thereby preventing a substantial escalation in battery degradation.

When comparing the cycle count of the EVs in AC and DC scenarios, we can observe that the range of cycle count in the different Δ SOC scenarios is significantly smaller for AC charging compared to DC charging. This implies that the influence of Δ SOC levels on cycle counts is less pronounced in AC charging than in DC charging. Furthermore, it is evident that most EVs have significantly more cycles with DC charging than with AC charging (up to +128%). Notably, the Kia EV6, Mercedes 350 EQE, Citroen C Zero, and Mitsubishi Outlander are exceptions, showing a decrease in cycle count from AC to DC charging. These are primarily the EVs with the highest C-rates (see Table 3).

It can be deduced that achieving optimal results for companies and EV owners depends on a well-balanced combination of battery capacity and C-rate. The careful balancing of these parameters is crucial to create a synergy that not only maximizes the profitability for individual EV owners, but also optimizes the company's economical interests in the context of V2G implementation. Fig. 8 shows a profitability matrix that provides insights into the recommended Δ SOC variations considering the interplay between C-rate and battery capacity of the EVs from the optimized scenarios. The matrix identifies an area of mutual benefit, revealing optimal charging strategies that increase profitability for both stakeholders involved. As the C-rate and battery capacity vary, the figure highlights the corresponding Δ SOC values that contribute to an economically beneficial scenario.

### 6.4. Summary discussion

When analyzing all cases and scenarios, the following results are striking:

- Cost and battery degradation analysis: When analyzing the costs and degradation of the batteries, it becomes evident that the sensitivity of the company's total annual costs relative to changes in the Δ SOC is a decisive factor. The choice between DC and AC charging plays a critical role in shaping these costs. The consistently lower cost profile of DC charging, due to its ability to provide a high C-rate during charging and discharging, underlines its economic advantages over AC charging. The company's total financial profits of EVs for DC charging ranged from €8838.96 (Δ SOC 0%) to −€1438.14 (Δ SOC 20%). In contrast, the total profit for AC charging had a narrower range, ranging only from €5467.37 to −€5145. The slightly higher degradation costs associated with DC charging are outweighed by the economic benefits, making it a more financially rewarding option for the company.
  Given the investment capital required, most companies choose not to establish a DC charging infrastructure in favor of the more cost-effective AC charging infrastructure. However, this situation underlines the importance of our analysis, which highlighted the benefits of DC charging. Although AC infrastructure dominates due to its lower initial costs, our analysis shows that despite the higher initial investment, the strategic implementation of DC charging stations can generate substantial returns for companies. This finding could be a compelling incentive for companies to strategically invest in DC charging infrastructure in the context of V2G integration.
  Furthermore, the linear inverse relationship between the company's profits and EV owners' profits as Δ SOC increases shows an interesting but small area of mutual benefit for both charging types.

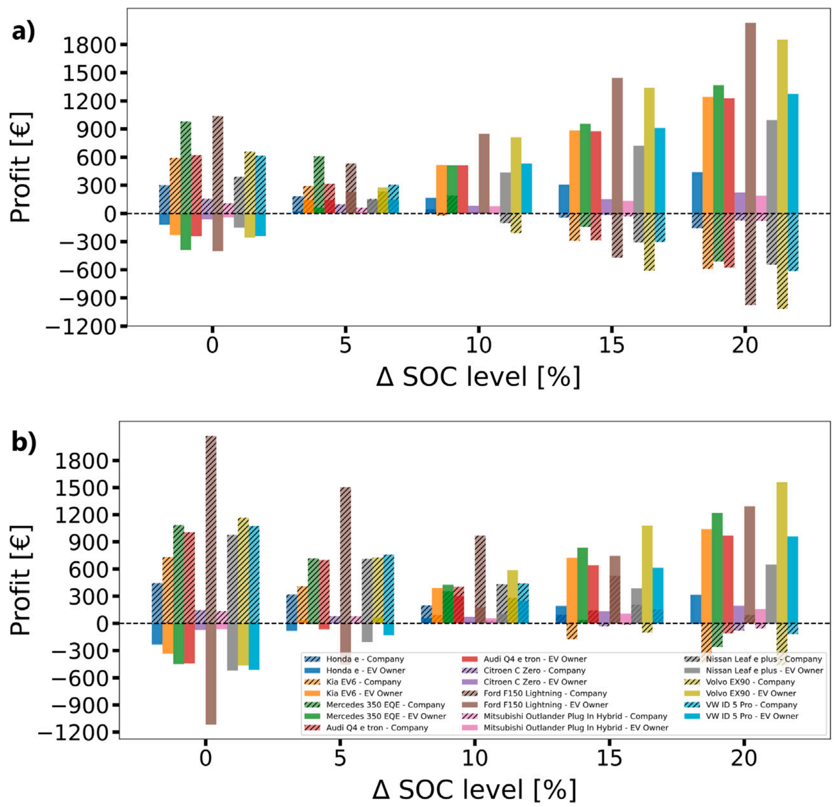

Fig. 6. Analysis of the financial benefits for the company and the owner of the EVs as a function of the $\Delta$ SOC level for the AC scenarios (a) and DC scenarios (b). The company's profits for each EV are hatched.

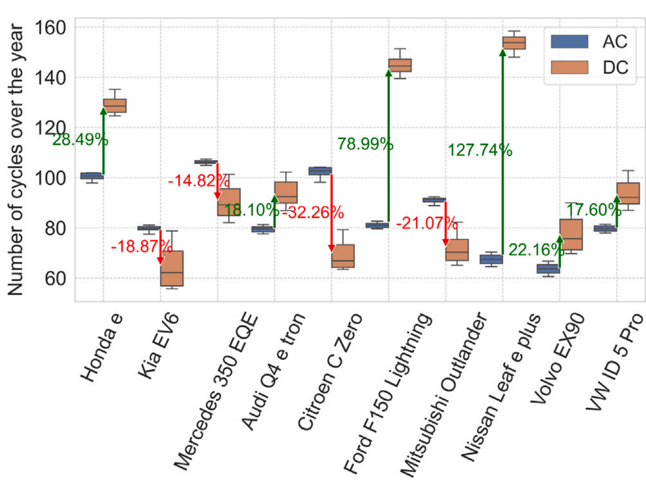

Fig. 7. Comparative boxplot analysis of the battery cycles of the 10 EVs under AC and DC charging. Each boxplot shows the distribution of full cycles for each of the 10 EV models, considering the different $\Delta$ SOC levels.

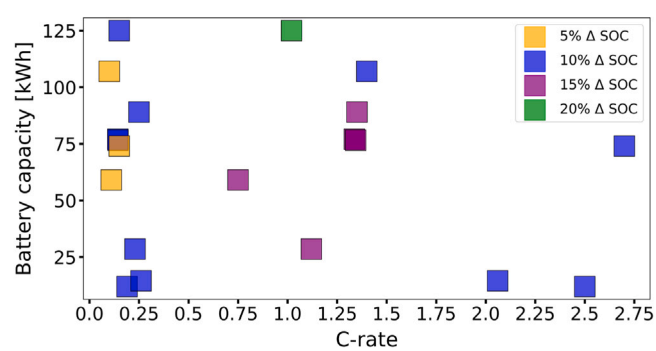

Fig. 8. Profitability matrix for recommended $\Delta$ SOC levels based on C-rate and battery capacity of EVs, revealing a mutually beneficial scenario.

- Pareto front analysis: Achieving a delicate balance between company profit and battery degradation proved to be a key factor in optimizing profitability for both the company and EV owners. The Pareto analysis highlighted the importance of an optimal $\alpha$-value, identified as 0.4 for DC charging scenarios and 0.5 for AC charging scenarios, and highlights an economic trade-off. This trade-off is an essential part of the sustainable integration of V2G technologies and emphasizes the balance between the profitability of the company and the longevity of the EV batteries. The calculated costs of the battery degradation model per kWh exchanged within certain ranges for AC and DC charging further emphasize the economic considerations. These ranges (€0.0176–€0.026/kWh for AC and €0.028–€0.0561/kWh for DC) provide decision makers with tangible metrics that provide insight into the cost dynamics of each charging scenario.
This differentiated understanding is essential to manage the complexity of V2G services and make informed decisions that are in line with both economic and sustainability goals.
- EV characteristic and model-specific analysis: AC Charging: For AC charging, high battery capacities are not necessarily good for company profits if the C-rate is low. The company has to provide more free electricity as the $\Delta$ SOC increases, but cannot fully utilize the high battery capacities. EV owners benefit more from lower battery degradation compared to the DC charging scenario. The company could make profits of €110.5 to €1037 per year depending on the vehicle model, assuming there is no

free charging for EVs (Δ SOC 0%). The loss range in a scenario with 20% free charging (Δ SOC of 20%) is between −€74.5 and −€975 per EV/year for the company. Owners of EVs, especially larger EVs, benefited more from AC charging resulting in a range of −€44 to −€400.6 per year after accounting for degradation costs in scenarios without free charging depending on the vehicle type. With a Δ SOC of 20%, EV owners generated profits of €190.22 to €2032 per year.
DC charging: For DC charging, larger battery capacities provide higher initial profitability for the company and maintain profitability at higher Δ SOC compared to AC charging. Conversely, the analysis shows that EVs with small battery capacities not only generate lower profits for the company, but also have limited flexibility to meet the company's electricity needs. This result raises the question of the feasibility of investing in charging infrastructure for small battery capacities. The company recorded higher profits in DC charging than in AC charging across each EV model, ranging from €135.2 to €2069 per year without free charging to profits of −€468 to €92.3 per year in a scenario with 20% free charging. For DC charging, owners benefited to a lesser extent than for AC charging and a higher C-rate proved beneficial as it mitigated battery degradation by reducing the number of cycles for several EV types. In this context, EV owners suffered losses of −€63.7 to −€1117.8 when there was no free charging available, and profits of €158.24 to €1559 with a Δ SOC of 20%.
- Cycle count: Most EVs have a higher cycle count for DC charging than AC charging, and the optimal outcome for companies and EV owners depends on a delicate balance between battery capacity and C-rate. EVs with small batteries not only generate significantly lower company profits but also endure high degradation, especially during DC charging. A considerably increased C-rate can be worthwhile for EV owners, as it prevents a significant increase in battery degradation by reducing the number of cycles (depending on fluctuations in the RTP as well as the battery degradation model), which is also a strategic consideration.

## 7. Conclusions

This study presents a comprehensive analysis of the integration of an EV fleet into an industrial smart grid, focusing on the optimization of operational flexibility, which considers both the reduction of electricity costs for the company and the degradation of individual EV batteries. The trade-offs between the company and EV owners are solved through multi-objective optimization. By applying the proposed approach, some noteworthy findings can be drawn, which are summarized below:

- The inherent trade-off holds the potential for mutual benefit between the two stakeholders (company and EV owners). Although there are no mutual losses, the area of mutual benefit is limited. The limited range of mutual benefit extends from a Δ SOC of 3% to 10% of the EV battery capacity for AC charging and from 6% to 17% for DC charging for providing the EV battery. Without DR optimization, one stakeholder could easily make a loss.
- Optimal Pareto $\alpha$-values ($\alpha = 0.4$ for DC, $\alpha = 0.5$ for AC) highlight an economic trade-off that is beneficial for both stakeholders. In these scenarios, minimizing energy costs to the company is weighted more evenly than minimizing battery degradation.
- DC charging was significantly more profitable and generated higher profits for the company than AC charging, as the battery capacity of larger EVs was used more efficiently due to the higher C-rate. Thus, DC charging proved to be 257.45% to 38.1% more profitable than AC charging, depending on the amount of free charging (Δ SOC).

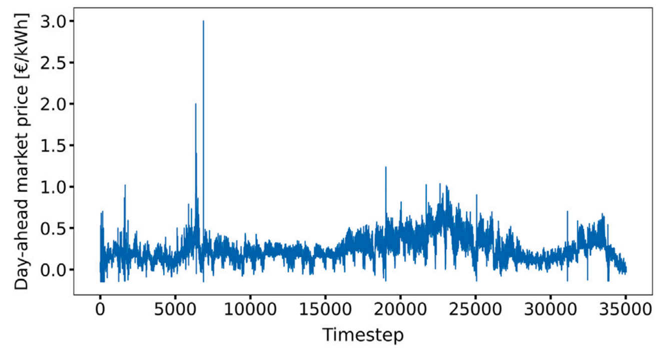


**Fig. A.1.** Day-ahead market prices for the German electricity market of the year 2022.

Overall, our study emphasizes the significant potential for V2G to reduce costs for employers while also providing benefits to EV owners, who are financially compensated for the increased battery degradation that occurs as a result of providing EVs for V2G. The results show that the profitability of EV owners varies widely, underlining the need for an equitable pricing strategy. EV owners' profit (the free or subsidized charging minus the degradation cost) should be proportionate to the value their EVs contribute to the operational and financial levels of the company. While the current remuneration methodology is a first step towards mutual profitability, it is not sufficient to develop a fair pricing paradigm that considers the heterogeneity of the value contribution of different EVs. This requires a forward-looking pricing mechanism that aligns EV owners' profit with the company's operational and financial benefits, promoting a harmonized and equitable framework for V2G integration.

## CRediT authorship contribution statement

**Andre Leippi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Markus Fleschutz:** Writing – review & editing, Software. **Kevin Davis:** Writing – review & editing, Methodology. **Anna-Lena Klingler:** Writing – review & editing, Methodology. **Michael D. Murphy:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

## 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.

## Data availability

The data that has been used is confidential.

## Acknowledgments

This research was performed as part of the MeSSO Research Group at the Munster Technological University (MTU). It was funded by the MTU Risam scholarship scheme, Ireland.

## Appendix

See Figs. A.1–A.6 and Table A.1.

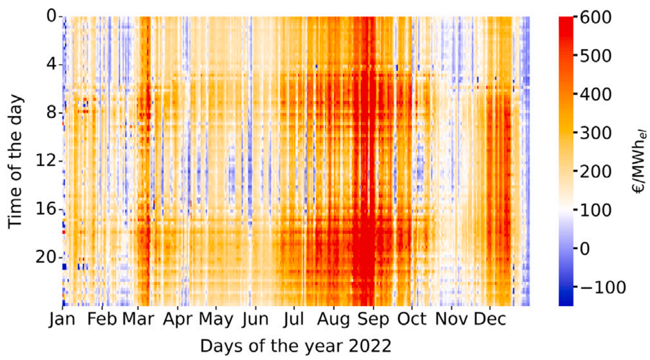


**Fig. A.2.** Historical 15 min electricity prices of the German electricity market of the year 2022.

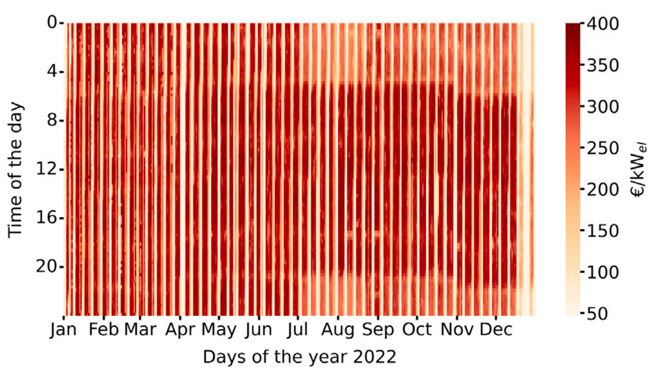


**Fig. A.3.** Heatmap of the load profile from the manufacturing company.

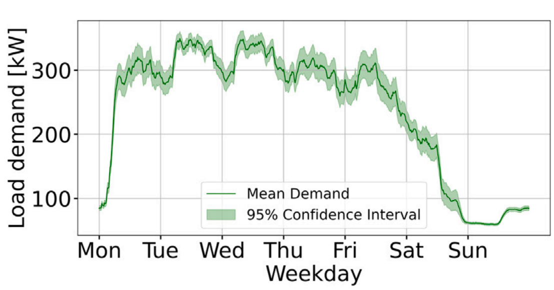


**Fig. A.4.** Company load demand for the average week and 95% confidence interval.

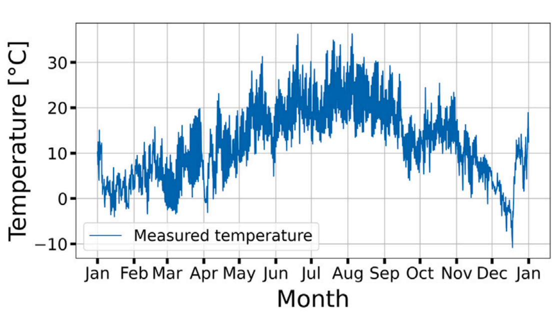


**Fig. A.5.** Measured ambient air temperature from the nearest weather station to the company.

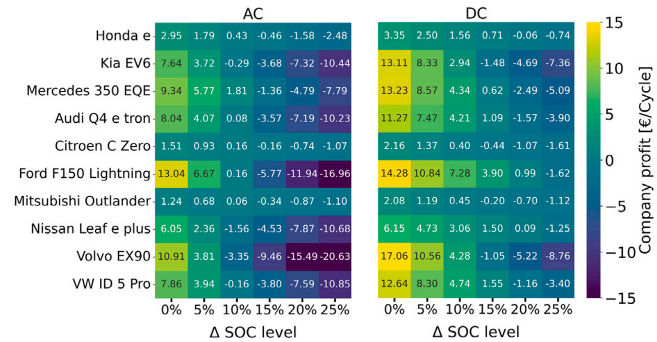


**Fig. A.6.** Analysis of the company profit per full cycle of the 10 EV models under different $\Delta$ SOC (0 to 25%) for AC and DC charging scenarios.

**Table A.1**
Cost and energy overview of the REF Case and Case 1 scenarios.

| Case description | Total annualized company costs [€] | Aggregated degradation costs [€] |
|---|---|---|
| REF: no EVs | 657,731 | 0 |
| Case 1: AC, 5% $\Delta$ SOC | 660,394 | 178 |
| Case 1: AC, 10% $\Delta$ SOC | 662,222 | 404 |
| Case 1: AC, 15% $\Delta$ SOC | 664,444 | 582 |
| Case 1: AC, 20% $\Delta$ SOC | 669,831 | 792 |
| Case 1: AC, 25% $\Delta$ SOC | 677,306 | 938 |
| Case 1: AC, 30% $\Delta$ SOC | 679,545 | 1047 |
| Case 1: DC, 5% $\Delta$ SOC | 659,621 | 312 |
| Case 1: DC, 10% $\Delta$ SOC | 662,557 | 693 |
| Case 1: DC, 15% $\Delta$ SOC | 664,738 | 992 |
| Case 1: DC, 20% $\Delta$ SOC | 666,980 | 1312 |
| Case 1: DC, 25% $\Delta$ SOC | 668,127 | 1463 |
| Case 1: DC, 30% $\Delta$ SOC | 670,024 | 1700 |

## References


[1] International Energy Agency (IEA). Global EV outlook 2023 – Analysis. 2023, https://www.iea.org/reports/global-ev-outlook-2023/executive-summary. [Accessed 13 July 2023].

[2] European Commission. A European green deal. 2020, https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en. [Accessed 13 July 2023].

[3] Heilmann C, Friedl G. Factors influencing the economic success of grid-to-vehicle and vehicle-to-grid applications—A review and meta-analysis. Renew Sustain Energy Rev 2021;145:111115. http://dx.doi.org/10.1016/j.rser.2021.111115, URL https://www.sciencedirect.com/science/article/pii/S1364032121004020.

[4] Ayón X, Gruber JK, Hayes BP, Usaola J, Prodanović M. An optimal day-ahead load scheduling approach based on the flexibility of aggregate demands. Appl Energy 2017;198:1–11. http://dx.doi.org/10.1016/j.apenergy.2017.04.038, URL https://www.sciencedirect.com/science/article/pii/S0306261917304324.

[5] Heffron Raphael, Körner Marc-Fabian, Wagner Jonathan, Weibelzahl Martin, Fridgen Gilbert. Industrial demand-side flexibility: A key element of a just energy transition and industrial development. Appl Energy 2020;269:115026. http://dx.doi.org/10.1016/j.apenergy.2020.115026, URL https://www.sciencedirect.com/science/article/pii/S0306261920305389.

[6] Ravi Sai Sudharshan, Aziz Muhammad. Utilization of electric vehicles for vehicle-to-grid services: Progress and perspectives. Energies 2022;15(2). http://dx.doi.org/10.3390/en15020589, URL https://www.mdpi.com/1996-1073/15/2/589.

[7] Chakir Asmae, Abid Meryem, Tabaa Mohamed, Hachimi Hanaa. Demand-side management strategy in a smart home using electric vehicle and hybrid renewable energy system. Energy Rep 2022;8:383–93. http://dx.doi.org/10.1016/j.egyr.2022.07.018, URL https://www.sciencedirect.com/science/article/pii/S2352484722012823, Technologies and Materials for Renewable Energy, Environment and Sustainability.

[8] Darcovich Ken, Recoskie Steven, Ribberink Hajo, Pincet Fleurine, Foissac Amaury. Effect on battery life of vehicle-to-home electric power provision under Canadian residential electrical demand. Appl Therm Eng 2017;114:1515–22. http://dx.doi.org/10.1016/j.applthermaleng.2016.07.002, URL https://www.sciencedirect.com/science/article/pii/S1359431116311176.

[9] Das Ridoy, Wang Yue, Putrus Ghanim, Kotter Richard, Marzband Mousa, Herteleer Bert, Warmerdam Jos. Multi-objective techno-economic-environmental optimisation of electric vehicle for energy services. Appl Energy 2020;257:113965. http://dx.doi.org/10.1016/j.apenergy.2019.113965, URL https://www.sciencedirect.com/science/article/pii/S0306261919316526.

[10] Duman A Can, Erden Hamza Salih, Gönül Ömer, Güler Önder. Optimal sizing of PV-BESS units for home energy management system-equipped households considering day-ahead load scheduling for demand response and self-consumption. Energy Build 2022;267:112164. http://dx.doi.org/10.1016/j.enbuild.2022.112164, URL https://www.sciencedirect.com/science/article/pii/S0378778822003358.

[11] Higashitani Takuya, Ikegami Takashi, Uemichi Akane, Akisawa Atsushi. Evaluation of residential power supply by photovoltaics and electric vehicles. Renew Energy 2021;178:745–56. http://dx.doi.org/10.1016/j.renene.2021.06.097, URL https://www.sciencedirect.com/science/article/pii/S0960148121009630.

[12] Küfeoğlu Sinan, Melchiorre Donato. Electric vehicles and batteries as domestic storage units in the United Kingdom. In: 2020 2nd international conference on smart power & internet energy systems. SPIES, 2020, p. 199–204. http://dx.doi.org/10.1109/SPIES48661.2020.9242948.

[13] Zafar Bassam, Slama Sami Abdullah Ben. PV-EV integrated home energy management using vehicle-to-home (V2H) technology and household occupant behaviors. Energy Strategy Rev 2022;44:101001. http://dx.doi.org/10.1016/j.esr.2022.101001, URL https://www.sciencedirect.com/science/article/pii/S2211467X2200195X.

[14] Zhou Kaile, Cheng Lexin, Wen Lulu, Lu Xinhui, Ding Tao. A coordinated charging scheduling method for electric vehicles considering different charging demands. Energy 2020;213:118882. http://dx.doi.org/10.1016/j.energy.2020.118882, URL https://www.sciencedirect.com/science/article/pii/S0360544220319897.

[15] Ramos Muñoz Edgar, Jabbari Faryar. A decentralized, non-iterative smart protocol for workplace charging of battery electric vehicles. Appl Energy 2020;272:115187. http://dx.doi.org/10.1016/j.apenergy.2020.115187, URL https://www.sciencedirect.com/science/article/pii/S0306261920306991.

[16] Powell Siobhan, Kara Emre Can, Sevlian Raffi, Cezar Gustavo Vianna, Kiliccote Sila, Rajagopal Ram. Controlled workplace charging of electric vehicles: The impact of rate schedules on transformer aging. Appl Energy 2020;276:115352. http://dx.doi.org/10.1016/j.apenergy.2020.115352, URL https://www.sciencedirect.com/science/article/pii/S0306261920308643.

[17] Seddig Katrin, Jochem Patrick, Fichtner Wolf. Integrating renewable energy sources by electric vehicle fleets under uncertainty. Energy 2017;141:2145–53. http://dx.doi.org/10.1016/j.energy.2017.11.140, URL https://www.sciencedirect.com/science/article/pii/S0360544217319989.

[18] Guo Jingli, Yang Jin, Cao Wenping, Serrano Clara. Evaluation of EV battery degradation under different charging strategies and V2G schemes. In: 8th renewable power generation conference. RPG 2019, 2019, p. 1–7. http://dx.doi.org/10.1049/cp.2019.0519.

[19] Ouammi Ahmed. Peak load reduction with a solar PV-based smart microgrid and vehicle-to-building (V2B) concept. Sustain Energy Technol Assess 2021;44:101027. http://dx.doi.org/10.1016/j.seta.2021.101027, URL https://www.sciencedirect.com/science/article/pii/S2213138821000370.

[20] Ioakimidis Christos S, Thomas Dimitrios, Rycerski Pawel, Genikomsakis Konstantinos N. Peak shaving and valley filling of power consumption profile in non-residential buildings using an electric vehicle parking lot. Energy 2018;148:148–58. http://dx.doi.org/10.1016/j.energy.2018.01.128, URL https://www.sciencedirect.com/science/article/pii/S0360544218301567.

[21] Dagdougui Hanane, Ouammi Ahmed, Dessaint Louis A. Peak load reduction in a smart building integrating microgrid and V2B-based demand response scheme. IEEE Syst J 2019;13(3):3274–82. http://dx.doi.org/10.1109/JSYST.2018.2880864.

[22] Chandra Mouli GR, Bauer P, Zeman M. System design for a solar powered electric vehicle charging station for workplaces. Appl Energy 2016;168:434–43. http://dx.doi.org/10.1016/j.apenergy.2016.01.110, URL https://www.sciencedirect.com/science/article/pii/S0306261916300988.

[23] Pang Chengzong, Kezunovic Mladen, Ehsani Mehrdad. Demand side management by using electric vehicles as distributed energy resources. In: 2012 IEEE international electric vehicle conference. 2012, p. 1–7. http://dx.doi.org/10.1109/IEVC.2012.6183273.

[24] Mehta R, Srinivasan D, Trivedi A. Optimal charging scheduling of plug-in electric vehicles for maximizing penetration within a workplace car park. In: 2016 IEEE congress on evolutionary computation. CEC, 2016, p. 3646–53. http://dx.doi.org/10.1109/CEC.2016.7744251.

[25] Tushar Wayes, Yuen Chau, Huang Shisheng, Smith David B, Poor H Vincent. Cost minimization of charging stations with photovoltaics: An approach with EV classification. IEEE Trans Intell Transp Syst 2016;17(1):156–69. http://dx.doi.org/10.1109/TITS.2015.2462824.

[26] van der Meer Dennis, Chandra Mouli Gautham Ram, Morales-España Mouli Germán, Elizondo Laura Ramirez, Bauer Pavol. Energy management system with PV power forecast to optimally charge EVs at the workplace. IEEE Trans Ind Inf 2018;14(1):311–20. http://dx.doi.org/10.1109/TII.2016.2634624.

[27] Wu Di, Zeng Haibo, Lu Chao, Boulet Benoit. Two-stage energy management for office buildings with workplace EV charging and renewable energy. IEEE Trans Transp Electr 2017;3(1):225–37. http://dx.doi.org/10.1109/TTE.2017.2659626.

[28] He Zhanwei, Khazaei Javad, Freihaut James D. Optimal integration of Vehicle to Building (V2B) and Building to Vehicle (B2V) technologies for commercial buildings. Sustain Energy, Grids Netw 2022;32:100921. http://dx.doi.org/10.1016/j.segan.2022.100921, URL https://www.sciencedirect.com/science/article/pii/S2352467722001667.

[29] Wang Dian, Sechilariu Manuela, Locment Fabrice. PV-powered charging station for electric vehicles: Power management with integrated V2G. Appl Sci 2020;10(18). http://dx.doi.org/10.3390/app10186500, URL https://www.mdpi.com/2076-3417/10/18/6500.

[30] Chandra Mouli Gautham Ram, Kefayati Mahdi, Baldick Ross, Bauer Pavol. Integrated PV charging of EV fleet based on energy prices, V2G, and offer of reserves. IEEE Trans Smart Grid 2019;10(2):1313–25. http://dx.doi.org/10.1109/TSG.2017.2763683.

[31] Ayyadi Soumia, Maaroufi Mohamed. Optimal framework to maximize the workplace charging station owner profit while compensating electric vehicles users. Math Probl Eng 2020;2020:1–12, URL https://api.semanticscholar.org/CorpusID:219682592.

[32] Beyazıt Muhammed Ali, Taşcıkaraoğlu Akın, Catalão João PS. Cost optimization of a microgrid considering vehicle-to-grid technology and demand response. Sustain Energy, Grids Netw 2022;32:100924. http://dx.doi.org/10.1016/j.segan.2022.100924, URL https://www.sciencedirect.com/science/article/pii/S2352467722001692.

[33] Honarmand Masoud, Zakariazadeh Alireza, Jadid Shahram. Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization. J Franklin Inst 2015;352(2):449–67. http://dx.doi.org/10.1016/j.jfranklin.2014.01.019, URL https://www.sciencedirect.com/science/article/pii/S0016003214000349, Special Issue on Control and Estimation of Electrified vehicles.

[34] Malya Prasad Prakash, Fiorini Laura, Rouhani Mohammadhadi, Aiello Marco. Electric vehicles as distribution grid batteries: a reality check. Energy Inf 2021;4. http://dx.doi.org/10.1186/s42162-021-00159-3, Funding Information: The research is partially funded by the Netherlands Organization for Scientific Research (NWO) under the MERGE (647.002.006) and NextGenSmart DC (629.002.102) projects. Publisher Copyright: © 2021, The Author(s)..

[35] Meenakumar Pragadeesh, Aunedi Marko, Strbac Goran. Optimal business case for provision of grid services through EVs with V2G capabilities. In: 2020 fifteenth international conference on ecological vehicles and renewable energies. EVER, 2020, p. 1–10. http://dx.doi.org/10.1109/EVER48776.2020.9242538.

[36] Zakariazadeh Alireza, Jadid Shahram, Siano Pierluigi. Multi-objective scheduling of electric vehicles in smart distribution system. Energy Convers Manage 2014;79:43–53. http://dx.doi.org/10.1016/j.enconman.2013.11.042, URL https://www.sciencedirect.com/science/article/pii/S0196890413007632.

[37] Tanguy Kevin, Dubois Maxime R, Lopez Karol Lina, Gagné Christian. Optimization model and economic assessment of collaborative charging using Vehicle-to-Building. Sustainable Cities Soc 2016;26:496–506. http://dx.doi.org/10.1016/j.scs.2016.03.012, URL https://www.sciencedirect.com/science/article/pii/S2210670716300439.

[38] Nguyen Hung Khanh, Song Ju Bin. Optimal charging and discharging for multiple PHEVs with demand side management in vehicle-to-building. J Commun Netw 2012;14(6):662–71. http://dx.doi.org/10.1109/JCN.2012.00032.

[39] Huang Shaotang, Liu Wei, Zhang Jiawei, Liu Cuicui, Sun Huiqin, Liao Qiangqiang. Vehicle-to-grid workplace discharging economics as a function of driving distance and type of electric vehicle. Sustain Energy, Grids Netw 2022;31:100779. http://dx.doi.org/10.1016/j.segan.2022.100779, URL https://www.sciencedirect.com/science/article/pii/S2352467722000923.

[40] Honarmand Masoud, Zakariazadeh Alireza, Jadid Shahram. Optimal scheduling of electric vehicles in an intelligent parking lot considering vehicle-to-grid concept and battery condition. Energy 2014;65:572–9. http://dx.doi.org/10.1016/j.energy.2013.11.045, URL https://www.sciencedirect.com/science/article/pii/S0360544213010153.

[41] Honarmand Masoud, Zakariazadeh Alireza, Jadid Shahram. Integrated scheduling of renewable generation and electric vehicles parking lot in a smart microgrid. Energy Convers Manage 2014;86:745–55. http://dx.doi.org/10.1016/j.enconman.2014.06.044, URL https://www.sciencedirect.com/science/article/pii/S019689041400569X.

[42] Wang Lu, Sharkh Suleiman, Chipperfield Andy. Optimal coordination of vehicle-to-grid batteries and renewable generators in a distribution system. Energy 2016;113:1250–64. http://dx.doi.org/10.1016/j.energy.2016.07.125, URL https://www.sciencedirect.com/science/article/pii/S0360544216310490.

[43] Ahsan Syed Muhammad, Khan Hassan Abbas, ul Hassan Naveed. Optimized power dispatch for smart building(s) and electric vehicles with V2X operation. Energy Rep 2022;8:10849–67. http://dx.doi.org/10.1016/j.egyr.2022.08.221, URL https://www.sciencedirect.com/science/article/pii/S2352484722016651.

[44] Toosi Hooman Ekhteraei, Merabet Adel, Al-Durra Ahmed, Swingler Andrew. Optimal battery cycling strategies in workplaces with electric vehicle chargers, energy storage systems and renewable energy generation. IET Renew Power Gener 2022;16(6):1121–33. http://dx.doi.org/10.1049/rpg2.12376, URL https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/rpg2.12376.

[45] Ma Tan, Mohammed Osama A. Optimal charging of plug-in electric vehicles for a car-park infrastructure. IEEE Trans Ind Appl 2014;50(4):2323–30. http://dx.doi.org/10.1109/TIA.2013.2296620.

[46] Zhou Tianpei, Sun Wei. Research on multi-objective optimisation coordination for large-scale V2G. IET Renew Power Gener 2020;14(3):445–53. http://dx.doi.org/10.1049/iet-rpg.2019.0173, URL https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-rpg.2019.0173.

[47] Leippi Andre, Fleschutz Markus, Murphy Michael D. A review of EV battery utilization in demand response considering battery degradation in non-residential vehicle-to-grid scenarios. Energies 2022;15(9). http://dx.doi.org/10.3390/en15093227, URL https://www.mdpi.com/1996-1073/15/9/3227.
[48] Leippi Andre, Fleschutz Markus, Davis Kevin, Murphy Michael D. Utilization of electric vehicle fleets in industrial demand response considering vehicle-to-grid benefits and battery degradation. In: 2022 18th international conference on the European energy market. EEM, 2022, p. 1–6. http://dx.doi.org/10.1109/EEM54602.2022.9921000.
[49] Saxena Saurabh, Xing Yinjiao, Kwon Daeil, Pecht Michael. Accelerated degradation model for C-rate loading of lithium-ion batteries. Int J Electr Power Energy Syst 2019;107:438–45. http://dx.doi.org/10.1016/j.ijepes.2018.12.016, URL https://www.sciencedirect.com/science/article/pii/S0142061518301212.
[50] Fleschutz Markus, Bohlayer Markus, Braun Marco, Murphy Michael D. Demand Response Analysis Framework (DRAF): An open-source multi-objective decision support tool for decarbonizing local multi-energy systems. Sustainability 2022;14(13). http://dx.doi.org/10.3390/su14138025, URL https://www.mdpi.com/2071-1050/14/13/8025.
[51] Gurobi Optimization, LLC. Gurobi optimizer reference manual. 2023, URL https://www.gurobi.com.
[52] Olmos Josu, Gandiaga Iñigo, de Ibarra Andoni Saez, Larrea Xabier, Nieva Txomin, Aizpuru Iosu. Modelling the cycling degradation of Li-ion batteries: Chemistry influenced stress factors. J Energy Storage 2021;40:102765. http://dx.doi.org/10.1016/j.est.2021.102765, URL https://www.sciencedirect.com/science/article/pii/S2352152X21004904.
[53] Lutsey Nic, Nicholas Michael. Update on electric vehicle costs in the United States through 2030. 2019, https://policycommons.net/artifacts/3810549/update-on-electric-vehicle-costs-in-the-united-states-through-2030/4616465/. [Retrieved 27 November 2023]. CID: 20.500.12592/gzw4p3.
[54] Das R. Multi-objective smart charge control of electric vehicles (PhD thesis), Newcastle upon Tyne, United Kingdom: Northumbria University; 2020.
[55] Ghotge Rishabh, Nijssen Koen Philippe, Annema Jan Anne, Lukszo Zofia. Use before you choose: What do EV drivers think about V2G after experiencing it? Energies 2022;15(13). http://dx.doi.org/10.3390/en15134907, URL https://www.mdpi.com/1996-1073/15/13/4907.
[56] Leippi Andre, Otteny Felix, Zernickel Melina, Klingler Anna-Lena. Power transfer vehicle-to-home (V2H). 2024, URL https://doi.org/10.24406/publica-2738.
[57] van Heuveln Koen, Ghotge Rishabh, Annema Jan Anne, van Bergen Esther, van Wee Bert, Pesch Udo. Factors influencing consumer acceptance of vehicle-to-grid by electric vehicle drivers in the Netherlands. Travel Behav Soc 2021;24:34–45. http://dx.doi.org/10.1016/j.tbs.2020.12.008, URL https://www.sciencedirect.com/science/article/pii/S2214367X20302519.
[58] Kostopoulos Emmanouil D, Spyropoulos George C, Kaldellis John K. Real-world study for the optimal charging of electric vehicles. Energy Rep 2020;6:418–26. http://dx.doi.org/10.1016/j.egyr.2019.12.008, URL https://www.sciencedirect.com/science/article/pii/S2352484719310911.
[59] Redondo-Iglesias Eduardo, Venet Pascal, Pelissier Serge. Measuring reversible and irreversible capacity losses on lithium-ion batteries. In: 2016 IEEE vehicle power and propulsion conference. VPPC, 2016, p. 1–5. http://dx.doi.org/10.1109/VPPC.2016.7791723.
[60] ENTSO-E. ENTSO-e transparency platform. 2022, https://transparency.entsoe.eu.
[61] Fleschutz Markus, Murphy Michael D. Elmada: Dynamic electricity carbon emission factors and prices for Europe. J Open Source Softw 2021;6(66):3625. http://dx.doi.org/10.21105/joss.03625.
[62] BDEW. BDEW-strompreisanalyse Juli 2023. 2023, https://www.bdew.de/service/daten-und-grafiken/bdew-strompreisanalyse/. [Accessed 15 September 2023].
[63] Fleschutz Markus, Bohlayer Markus, Braun Marco, Murphy Michael D. From prosumer to flexumer: Case study on the value of flexibility in decarbonizing the multi-energy system of a manufacturing company. Appl Energy 2023;347:121430. http://dx.doi.org/10.1016/j.apenergy.2023.121430, URL https://www.sciencedirect.com/science/article/pii/S0306261923007948.
[64] Sabillón Antúnez Carlos, Franco John F, Rider Marcos J, Romero Ruben. A new methodology for the optimal charging coordination of electric vehicles considering vehicle-to-grid technology. IEEE Trans Sustain Energy 2016;7(2):596–607. http://dx.doi.org/10.1109/TSTE.2015.2505502.
[65] Mobility House LLC. Vehicle-to-grid: Elektroauto als stromspeicher nutzen. 2023, https://www.mobilityhouse.com/de_de/vehicle-to-grid. [Accessed 26 September 2023].
[66] EV Database. EV database. 2023, https://ev-database.org/. [Accessed 28 July 2023].