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Review

A Review of EV Battery Utilization in Demand Response Considering Battery Degradation in Non-Residential Vehicle-to-Grid Scenarios

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Abstract: Integrating fleets of electric vehicles (EVs) into industrial applications with smart grids is an emerging field of important research. It is necessary to get a comprehensive overview of current approaches and proposed solutions regarding EVs with vehicle-to-grid and smart charging. In this paper, various approaches to battery modeling and demand response (DR) of EV charging in different decentralized optimization scenarios are reviewed. Modeling parameters of EVs and battery degradation models are summarized and discussed. Finally, optimization approaches to simulate and optimize demand response, taking into account battery degradation, are investigated to examine the feasibility of adapting the charging process, which may bring economic and environmental benefits and help to alleviate the increasing demand for flexibility. There is a lack of studies that comprehensively consider battery degradation for EV fleets in DR charging scenarios where corresponding financial compensation for the EV owners is considered. Therefore, models are required for estimating the level of battery degradation endured when EVs are utilized for DR. The level of degradation should be offset by providing the EV owner with subsidized or free electricity provided by the company which is partaking in the DR. This trade-off should be optimized in such a manner that the company makes cost savings while the EV owners are compensated to a level that is at least commensurate with the level of battery degradation. Additionally, there is a lack of studies that have examined DR in smart grids considering larger EV fleets and battery degradation in multi-criteria approaches to provide economic and environmental benefits.

Keywords: multi-objective optimization; electric vehicle fleet; electric vehicle charging; industrial demand response; vehicle-to-grid; smart grid; battery degradation

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1. Introduction

In an effort to achieve climate neutrality by 2050, the European Commission has decided to design the European climate, energy, land use, transport, and taxation policies in such a way that net greenhouse gas emissions can be reduced by at least 55% by 2030 compared to 1990 levels. For this purpose, the Climate Change Regulation formulates the objectives in the transport sector that complement emissions trading. A key milestone in the development of the transport sector will be stricter CO_2 emission standards for passenger cars and light commercial vehicles, which will accelerate the transition to zero-emission mobility, as the average annual emissions of new vehicles will have to be 55% lower from 2030 and 100% lower from 2035 compared to 2021 levels [1]. Therefore, all new cars registered from 2035 onwards will be zero-emission. It will also ensure that drivers can charge or refuel their vehicles on a reliable network across Europe by increasing charging capacities in line with the sales of zero-emission vehicles and by setting up charging and refueling stations at regular intervals on major highways [2]. The substitution of internal combustion engine vehicles (ICEVs) with EVs provides a promising opportunity for countries' transportation systems to meet CO_2 reduction commitments and thus mitigate climate change and air pollution. Therefore, it is important to study the global emissions of EVs compared to ICEVs from a whole life cycle perspective, e.g., using the widely applied life cycle analysis method [3,4].

In [5], current and future electric vehicles were studied in terms of environmental impact. The results show that in the future scenario, EVs are generally preferable to PHEVs and ICEVs in the context of environmental impact for the same lifetime and vehicle characteristics. In general, previous studies show that EVs are suitable, at the local level, to create less pollutant emissions than ICEVs in the transport sector [4–7]. As a result, governments in many European countries are promoting electric mobility, which has already led to a substantial increase in electric vehicles over the last several years. The European market for EVs experienced significant growth in 2020. More than 1.36 million new electric passenger cars, including battery electric vehicles (BEVs) and plug-in hybrids (PHEVs), were sold across the region. This represents an increase of 143% compared to 2019. In this paper, for the sake of simplicity, battery electric vehicles (BEVs) are referred to as electric vehicles (EVs). While the share of EVs in the total passenger new car market was around 2% in 2018, it increased from 4% to more than 11% between 2019 and 2020 [8]. In the European core regions, the EV market grew by 147% year-on-year in the first half of 2021 to a total of 336.000 BEVs sold. PHEV sales increased by 248% to 350.000 units. Germany dominates the market in Europe with 44% of all BEV sales and 47% of PHEV sales in the five European core markets in the first half of the year [9].

Due to the ongoing trend, it is essential to deal with the increasing number of EVs, as both the electrical load and the demand on the electricity markets increase. According to the Global EV Outlook 2021 [10], the global EV fleet across all modes (excluding two- and three-wheelers) will increase from over 11 million in 2020 to nearly 145 million vehicles by 2030. This corresponds to an annual average growth rate of almost 30%. Furthermore, EVs will account for approximately 7% of the road vehicle fleet in 2030, and EV sales will reach almost 15 million in 2025 and over 25 million in 2030, representing 10% and 15% of all road vehicles sold, respectively. As electricity generation based on renewable resources requires flexibility on the consumer side, the electricity market is expected to adopt more dynamic electricity prices to incentivize demand response. To take advantage of this price volatility, companies could implement vehicle-to-grid (V2G) and flexible smart charging in the manner of a service provider. A major challenge is to integrate fleets of EVs into smart grids, as stakeholders need to be able to manage the charging and discharging of EV fleets in a way that achieves economic, technological, and environmental benefits. With the use of renewable energy generation and different price signals in electricity markets mainly due to the synergistic use of renewables and EVs, certain stakeholders could achieve several benefits. In terms of an industrial or non-residential setting, these stakeholders are the industrial-based electricity-consuming companies that may be able to utilize EVs as mobile and low-cost electricity storage. The EV owner (employee of the company) can be compensated for providing their vehicle batteries as temporary storage. The electricity grid operator will benefit, as the penetration of intermittent renewable energy sources will be more easily facilitated. EV owners' concerns about battery degradation should be appropriately addressed so that an optimal trade-off between increasing economic performance for demand response for the company and financially compensating EV owners at a level that is at least equal to the battery degradation endured. To represent the trade-off between these stakeholders in the industrial setting, who would not necessarily collaborate, multi-criteria optimization problems can be constructed to simulate one or more (partly competing) objectives. Namely, minimizing the company's electricity costs, CO_2 emissions, and EV battery degradation costs.

Therefore, effective methods are needed to improve the economic and environmental use of the growing supply of EVs. As such, this study focuses on critically evaluating the published literature dealing with the following three main components: demand response in non-residential settings, optimization of different and competing objectives, and the analysis of battery degradation in EV charging scenarios. The inclusion of battery degradation is essential in achieving a more realistic modeling environment. Many EV owners do not want their EVs used for demand response participation as the many charging and discharging cycles that take place over a given period will ultimately reduce the capacity of their EV battery due to degradation, even if a short-term economic gain is achieved. In this context, Huang et al. [11] investigated which preferences Dutch EV drivers have for participation in V2G contracts. The results show that Dutch EV drivers are most concerned with discharge cycles. It was also found that Dutch EV drivers prefer a higher monthly remuneration for providing their EV and a higher guaranteed minimum battery state of charge (SOC). The SOC is a percentage value and is calculated as the ratio of the net capacity to be discharged and the nominal capacity of the battery [12].

Geske and Schumann [13] also investigated the willingness to participate in V2G using a representative sample of vehicle users in Germany. Similar to [11], they found that range anxiety and minimum range emerged as the most important factors affecting vehicle users' willingness to participate in V2G. Furthermore, their analysis showed that high remuneration is not necessary for significant participation rates if the V2G concept is convincing and provides enough room for unpredictable and predictable mobility demand. Most EV owners and grid operators cannot quantify the trade-off that exists between utilizing the untapped capacity of EVs for smart grid demand response utilization and the resulting reduced capacity of the EV batteries as a result of increased utilization and therefore battery degradation. The different objectives should be simulated depending on the individual interests of the stakeholders in order to control the charging and discharging of EVs in the best way to optimize economic and environmental benefits.

The contribution of this work is to provide an overview of the current state of battery modeling and optimization strategies in V2G and smart charging scenarios of EVs. In particular, the interaction of the three main components mentioned above is investigated to identify gaps in the utilization of EV batteries in an industrial DR for future research. This review is structured as follows. Section 2 briefly explains the methodology used in the literature review. Section 3 explores research studies that focus on non-residential demand response. Section 4 summarizes different approaches to battery modeling and charging parameters in different EV charging scenarios. Section 5 focuses on battery degradation and different battery degradation models. Section 6 presents modeling approaches that already consider battery degradation as well as different optimization targets. After a presentation of the current state of the art in the field of optimal control of EV charging and discharging in the context of demand response and battery degradation, Section 7 discusses the identified gaps in the field of EV charging. Section 8 provides a concise conclusion to this review.

2. Methodology

We first reviewed the sections on non-residential DR, EV battery modeling, and battery degradation. Then, the interactions between these components were examined to identify gaps in the use of EV batteries for economic and environmental benefits. In conducting this review, we proceeded in three steps. In the first step, we formulated preliminary research topics or research questions: the goal was to broadly examine the status of EV battery use in demand response, taking into account battery degradation.

The second step was to select the digital libraries of the studies and the timeframe. The following digital libraries were searched for the review: Google Scholar, MDPI, Scopus, IEEE Xplorer, ScienceDirect, Springer, and Elsevier. For the databases, we used a set of including and excluding keywords. The following two exclusionary criteria were generally used: we limited the search to English-language references and to those published since 2013. Due to the relatively innovative and novel concept of V2G regarding the integration of electric vehicles into smart grids, we chose this time period because most electric vehicles on the market today, as well as many EVs coming to market in the next few years, are not bidirectional or V2G capable [14]. Nowadays, there are still only a few EVs V2G capable such as the Nissan Leaf [15], the Mitsubishi Outlander [16], or the Kia Soul [17]. Nevertheless, the development is heading in the direction of a more grid-interactive network system. For example, all Volkswagen ID models with the 77 kWh battery will be enabled for V2G technology in the future [18].

The third step was to select and analyze the literature. We searched the above databases for studies, reviews, summaries, keywords, and full texts for the terms such as "Electric Vehicle *", "Vehicle-to-Grid", "Demand Response", "Smart Charging", "Smart Grids" and their abbreviations. For Table 1 ("Battery modeling and charging parameters found in the literature"), the selection criteria were broad and included studies published on EV charging or charging strategies to provide an overview of the state of the art on battery modeling and charging parameters. Optionally, keywords such as "V2G", "Renewable Energy", "Battery Degradation" or "CO_2 Emissions" were included in the search.

For Table 2 ("Battery degradation models"), empirical, semi-empirical, and electrochemical/mechanical degradation models were reviewed to investigate the impact of different influencing parameters from different perspectives. The focus was on studies addressing "cyclic battery degradation"; studies addressing calendar degradation were not explicitly searched.

For Table 3 ("Optimization scenarios in smart grids considering battery degradation"), keywords such as "Multi-Objective Optimization", "Optimization", "Batteries" and "Energy arbitrage" were included in addition to the keywords from the search in Table 2. In addition, only studies that included any form of cyclic battery degradation for energy storage (EV or BESS) were included. Therefore, the keywords "degradation" or "battery degradation" were required. BESSs were also included as it was found that there were few studies in this area. The keyword "Demand Response" was only optionally included in the search for the same reason. Although some studies consider price-based DR with different tariffs and different prices or incentive-based DR, a large gap was apparent in this field when the term "Demand Response" was added (especially in combination with "Industry" or "Commercial").

3. Non-Residential Demand Response

In this work, we focus on DR for non-residential buildings where employees work. This is typically the case in the industrial and commercial sectors including industrial and large commercial firms as well as public sector organizations (see also [19]).

DR is the provision of demand-side flexibility by a final electricity consumer to the electricity system either by reacting voluntarily to price signals (price-based DR) or reacting to specific requests (incentive-based DR) [20]. Driven by digitalization and the trend towards decentralization within the energy transition, DR is a cost-effective alternative to other flexibility sources, such as storage or grid expansion [19,21]. Consequently, as the electricity system's demand for flexibility is expected to quadruple by 2050, DR is becoming increasingly important [22]. DR is a key element for the integration of fluctuating renewable energy sources in the electricity system, which is a major challenge in the renewable energy transition [21,23]. The high relevance of DR is reflected by intense research activities [24] and numerous research projects funded at European [25–27] and national levels [28–30]. The research on DR can be classified by the sectors of electricity users: the residential, commercial, and industrial sectors [19]. However, when only cross-sectional technologies are considered, industrial companies can be grouped with large commercial companies (e.g., [31]). Similarly, small commercial businesses can be grouped with the residential sector due to their similar electricity consumption (e.g., [32]). This is also reflected in the electricity end-user categorization [19]. Although the theoretical potential of the three sectors is estimated to be similar in magnitude [33], the commercial sector gains less scientific attention than the others [19,34].

Traditionally, only the industrial sector has been able to participate in DR schemes [35]. Due to large equipment dimensions and the existence of advanced IT infrastructure, industrial DR can often be applied without high investments and has therefore been especially promising [36]. However, since the advent of flexibility aggregators, the commercial and residential sectors also have access to DR programs, albeit only indirectly. Other barriers to DR deployment are expected to be gradually removed as the demand for flexibility in the power system increases. Moreover, by installing on-site renewable energy sources, more and more electricity consumers become prosumers. Assuming a price gap between purchasing and feed-in electricity price, these prosumers can directly benefit from their demand-side flexibility that enables them to optimize their energy demand and feed-in profile and reduce electricity costs as a result.

Over the last three decades, research in the field of non-residential DR potentials and modeling has been steadily intensified, resulting in a large and growing body of literature.

Most of the studies focus on industrial production processes (e.g., [37–40]) while fewer on cross-sectional technologies such as distributed energy resources [41] (e.g., combined heat and power [42–44], stationary battery storage [45]), air separation [46] and heat upgrading technologies (e.g., electric heat pumps [31,47]) in industrial and commercial buildings. For some recent reviews on industrial DR, the reader is referred to [19,24,34,36,48,49].

Despite a large number of studies on DR that incorporate EVs, the literature lacks a focus on the potential of utilizing the employee's EV batteries to shape the demand profile of an employer.

A recent study by Shahnewaz Siddiquee et al. [48] conducted a comprehensive literature review on research trends, current implementation state, and adoption barriers of industrial DR. The study particularly highlighted significant potentials in large industries such as aluminum, cement, and food. As the main barriers to the application of industrial DR, the study identified the lack of access to information, technical constraints, but also lacking financial mechanisms, and DR promoting policies. Here, the lacking information access was primarily an insufficient knowledge about the available flexibility. To solve this problem of quantifying the specific DR potential, model-based approaches can be used which are usually based on simulation, metaheuristics, or mathematical optimization [50].

4. Battery Modeling

In the literature, there are different approaches to model individual EV or EV fleets to take advantage of the multiple benefits of V2G and smart charging. In energy management systems, the charging and discharging process of an EV is characterized by the dynamics of its battery state. Batteries are modeled by a dynamic SOC equation. Thereby, the EV battery is mostly simulated as a temporarily available energy storage system that is subject to technical constraints such as capacity and temporal restrictions. In general, the modeling of EV batteries and their charging characteristics can be divided into two basic categories. One is a model where the battery of each vehicle is modeled individually. Here, EV aggregators are often used to control and manage the SOC, charge or discharge, and communication of all EVs to represent them on an aggregate level for the power exchange between the vehicle, the grid, and the demand. While optimizing the charging/discharging of individual EVs is more complex and time-consuming, it can still address the needs and potential V2G contracts of EV owners. Flexible and practical strategies can be integrated such as desired SOCs or minimum EV range at specific times for individual EV owners. The other is a model in which the batteries of an often large number of individual EVs in a vehicle fleet are combined into a single aggregate battery, which clusters the EVs and represents them as one virtual battery. In this case, this model usually has only a single state of charge variable and enables efficient optimizations with reduced computational expenses.

Table 1 summarizes different charging and objective implementations, the type of battery modeling, the number of EVs considered, and various battery modeling parameters such as charging and discharging efficiencies, SOC restrictions, and C-rates of different EV charging scenarios. In addition, we investigated which studies have taken into account the following aspects: the possibility of V2G, the integration of renewable energy, and the consideration of CO_2 emissions and battery degradation. The C-rate is a measure of the maximum rate at which a battery is charged or discharged in relation to its maximum capacity. A C-rate of 1 means that the battery can be completely discharged in 60 min, and 0.5 C equals to 120 min. In the 23 studies reviewed, as well as in most charging control strategies in the literature, electric vehicles are modeled individually. Only a few studies use a single aggregated battery with common variables or parameters, as these represent limited conditions for charge control. Thus, the state and status of each vehicle's battery can be integrated as a direct constraint for charging optimization. The studies reviewed focused primarily on the analysis of:

- Charging optimization strategies: There are various strategies that regulate the charging behavior of EVs. These include uncontrolled and controlled charging. In the case of uncontrolled charging, the simulations (Table 1) often assume a charging behavior of "as fast as possible". In this behavior, the EV starts charging immediately when it is connected to the grid and stops charging as soon as a certain SOC is reached (e.g., a fully charged battery) or when the vehicle leaves the charging station. In coordinated charging, the EVs' charging loads are intelligently controlled and managed (smart charging) to minimize charging costs through a dynamic pricing policy.
- Benefits of additional services that EVs can provide: These are consistent with the benefits of the V2G concept, including reducing grid congestion concerns (peak shaving and load balancing through valley filling). They offer ancillary services such as voltage and frequency regulation through cheap and fast energy storage, possible support for renewable energy sources, and use as spinning reserves [51,52].
- Increasing the techno-economic potential of EV microgrids or smart grids including energy arbitrage: Aside from reducing utility operating costs, revenues can be generated using EVs. This includes V2G energy arbitrage, where electricity is bought from the grid and temporarily stored in the EV when the electricity price is low. Then the excess energy is sold to the grid when the price of electricity is considered high. Another way to make profits is the so-called "Beneficial V2G". This involves deliberately discharging and then recharging a battery during the performance of V2G services to reduce overall battery degradation [53,54]. Therefore, the reciprocal effect of several factors such as minimizing energy costs, accounting for battery degradation, CO_2 emissions, and, in this context, the inclusion of renewable energy sources should be considered to weight these competing objectives.

Table 1. Battery modeling and charging parameters found in the literature.

Study	V2G	RES	Degr.	CO_2	Battery Modeling	Number of EVs	(Dis)Charge Efficiency	SOC Limits	(Max) C-Rate
Malya et al. (2021) [54]	√	×	√	×	1EV	1	0.85–(up to 1)	≥10%	22 kW (1 C)
Cardoso et al. (2014) [55]	√	√	√	√	AB	1080	0.9	≥20%	11 kW (0.45 C)
Di Giogio et al. (2014) [56]	√	×	×	×	XB	63	0.98	20–90%	19.8 kW (0.9 C)
Liu et al. (2015) [57]	×	√	×	×	XB	60	n/a	Objective SOC 85%	0.5 C
Zhongjing, Ma et al. (2015) [58]	×	×	√	×	XB	1000	n/a	15–90%	n/a
Skugor and Deur (2015) [59]	×	√	×	×	AB	10	0.92	0–100%	10 kW (0.625 C)
Wang and Infield (2015) [60]	√	×	√	×	XB	42	0.9–0.93	20–100%	−2.16 kW and +2.4 kW
Nguyen et al. (2015) [61]	√	√	×	×	XB	600	n/a	n/a	2.88 kW and 7.68 kW
Zhang et al. (2017) [62]	√	×	√	×	AB	5000	0.92	≥40%	3.3 kW (0.1375 C) and 6.6 kW (0.275 C)
Peng et al. (2017) [63]	√	×	×	×	XB	10	n/a	20–95%	10–14 kW (0.4 C–0.625 C)
Wu et al. (2017) [64]	√	√	×	×	1EV	1	0.9	20–90%	3.6 kW and 10 kW (0.1 C–0.7 C)
Mouli et al. (2017) [65]	√	√	√	×	XB	6	0.95	5 kW–80%	−10 kW and +50 kW (0.5 C–0.66 C)
Ramadan et al. (2018) [66]	√	×	×	×	XB	300	n/a	>40%	4 kW (0.16 C)
Tavakoli et al. (2018) [67]	√	√	×	×	XB	100	(0.9), 0.95	20–100%	4 kW (0.2 C)
Turker and Colak (2018) [68]	√	√	×	√	1EV	1	n/a	10–100%	10 kW (0.3 C)
Bucić et al. (2018) [69]	√	×	×	×	XB	25	(0.75), 0.9	20–90%	3.5 kW (0.35 C), 50 kW (fleet)
Ahmadian et al. (2018) [70]	√	√	√	×	XB	15	0.9	dep = 100%	n/a
Vuelvas et al. (2020) [71]	×	×	×	×	AB	1000	0.9	n/a	3 kW (0.25 C)
Cheng et al. (2020) [72]	√	√	×	×	XB	10	n/a	>20%	9.6 kW
Li et al. (2020) [73]	√	√	√	×	XB	200, 400, 500	n/a	12–94%,	7 kW (0.16 C)

Table 1. *Cont.*

Study	V2G	RES	Degr.	CO_2	Battery Modeling	Number of EVs	(Dis)Charge Efficiency	SOC Limits	(Max) C-Rate
Das et al. (2020) [74]	√	√	√	√	XB	10	0.9	≥20%	3 kW (0.1 C)
Sepetanc et al. (2021) [75]	×	×	√	×	CB	100	0.9–0.93	≥20%	1 C
Essiet and Sun (2021) [76]	√	×	√	×	CB	5 × 300	0.95	10–90%	6.6 kW (0.165 C)

V2G = vehicle-to-grid; RES = renewable energy sources; Degr = electric vehicle battery degradation considered; CO_2 = CO_2 emissions; 1EV = only 1 EV; AB = aggregated battery with a single state-of-charge state variable; CB = cluster-based battery; XB = several individual batteries; SOC = state of charge; n/a = information not available; kW = kilowatt; dep = minimal departure SOC.

The charging and discharging efficiencies of the examined papers, as displayed in Table 1, are approximately 90% with a charging power in the range of about 3–10 kW. The C-rates are in the range of 0.1 to 1 C. In [77], based on several studies examined, it was assumed that a range between 2 C and 5 C was realistic for the maximum C-rate for EVs, yet a higher C-rate increases battery degradation and thus significantly affects the life cycle of a battery (Table 2). For this reason, there are very few studies on optimizing the charging of EVs with very high C-rates. However, the assumed values depend strongly on the vehicle types and the maximum charging rates of the charging stations. SOC limits range from 0 to 100%, often assuming a lower limit of 20% and an upper limit of approximately 85 to 95%. This is first to account for unexpected trips and second to avoid a higher depth-of-discharge (DOD) of the EV battery, as this degrades the battery faster [78]. DOD is the difference in SOC in a cycle (a cycle between 30 and -80% SOC means 50% DOD). The number of EVs simulated depends primarily on the study objective and the battery model. Most studies tend to investigate bidirectional charging in the domestic setting. In the aggregated battery model with only one single-state-of-charge variable, larger fleets of EVs are modeled more often. As V2G and, consequently, load management of EVs are typical demand-side management issues, the charging activity of EVs is influenced by dynamic price-based systems (real-time pricing (RTP), time of use, critical peak pricing, and peak time rebates). According to Amin et al. [79], it appears that most of the research related to EV charging has been conducted in the RTP environment. With this dynamic tariff, the electricity price changes in a regular time interval depending on the grid load to represent the real-time structure. Therefore, the RTP price type seems to be superior to all other systems and provides a solid platform to represent EV charging scenarios in a demand response environment.

4.1. Single Aggregate Battery

The introduction of clusters in aggregated models is an approach for numerically efficient solutions in EV fleet planning and optimization. In this technique, contrary to aggregated battery models, multiple flexible and practical strategies can be integrated as EVs are assigned to clusters in self-defined sizes. In [76], the clusters described integer variables to which an arbitrary number of EVs were assigned, facilitating the scaling of large vehicle fleets. Here, the cluster structure consists of 21 clusters ranging from 0% to 100% SOC (5% SOC each). Another model that has low computational complexity, as well as lower real-time communication requirements, is the reduced state-space model proposed in [80]. This model, based on the state-space method, describes aggregated EVs with different connection states and different SOCs and predicts state transitions and control capacity estimation using the Markov state transition method. Cardoso et al. [55] modeled the EV fleet (up to 1080 EVs) using a new EV aggregator model and a stochastic extension for schedule uncertainty with four battery sub-models to analyze investment decisions in a large office building.

To achieve this, the EVs in a fleet are distributed to one of four characteristic states (at home, connected to the microgrid, driving home, and driving to the microgrid) at each time step, where all variables related to the operation of the EV are explicitly computed in each time step. Škugor and Deur [59] modeled a fleet of 10 EVs as a single aggregate battery with only the SOC as a state variable for energy planning. Their dynamic programming approach provides a globally optimal solution with a relatively low computational load due to the low order of the aggregate battery model. In [62], a heuristic intelligent charging strategy for a V2G fleet with aggregated parameters was created to represent the energy and power constraints of an entire EV fleet (5000 EVs were aggregated). Here, instead of predicting individual load profiles or individual charging requirements, the aggregated energy and power constraints of the V2G fleet were captured and predicted via power load profile predictions, time series and probabilistic predictions to be subsequently implemented using a smart charging strategy. In [71], a virtual battery model was used to represent the energy storage and energy demand flexibility capability of a vehicle fleet. This virtual battery represents the total capacity and total flexibility of this fleet and is represented as a dynamic model with stochastic energy demand characterized by different energy consumption scenarios. When the characteristics of EV owners are grouped into behavioral clusters, EV groups with similar demand profiles can be generated without the need for detailed models or measurements of EVs. This approach allows the aggregate flexibility of a potentially large number of EVs to be described with a simple first-order model without dealing with the complexity of individual participants' behavior.

4.2. Individual Modeling

In the second type of battery modeling, where each EV is simulated individually, there are also different optimization approaches. For example, ref. [56] simulated a sequential arrival of 63 EVs whose charging profiles can be rescheduled at any time. Hence, each EV has a different predefined initial state of charge, arrival and departure time, and a desired final state of charge. For a realistic and variable pattern, the arrival times are chosen randomly so that the average arrival frequency is piecewise constant. The dwell time, as well as the desired end state, correspond to a predefined mean value plus a randomly chosen number within a certain adjustable range.

As with the aggregated virtual battery, probabilistic predictions (normal distribution, two-parameter Weibull distribution, Poisson distribution, Monte Carlo simulations) are applied for arrival and departure times, SOCs (e.g., for minimum, maximum, initial, desired), and driving patterns. Another option involves gathered vehicle data from people to create daily activity profiles with hourly load profile data and driving patterns. In most studies, depending on these parameters and conditions, each EV is simulated individually. The capacity and the charging demand of the EVs are regulated in an aggregator, which is responsible for managing and controlling the charging of EVs, in order to obtain overall economic and environmental results with respect to the optimization goal. The aggregator can also contribute to voltage and frequency support, load balancing and reducing power losses of the EV batteries [78].

In addition, the individual battery simulation provides the opportunity for each EV to implement its own optimal charging strategy while considering battery degradation, to maintain stakeholder and/or customer satisfaction. In [58], 1000 EVs were simulated individually, and the trade-off between the total generation cost and the cumulative battery degradation cost as a function of charging power was studied, while renewable energy and the possibility of V2G were not considered. Li et al. [73], on the contrary, simulated an energy management strategy with the deployment of a photovoltaic (PV) system and an additional battery energy storage system (BESS) for a large EV charging station (200, 400, 500 EVs). As in most studies, battery degradation was considered either as a linear model with a fixed degradation rate [60,62,73] or integrated with EV costs [55] in their economic analysis of cost per kWh cycle. As in [70], the degradation cost was solely integrated into the objective functions, while minimizing the battery degradation cost is seldom considered as an optimization process for EV charging. Similarly, CO_2 emissions were reduced by optimizing the increasing penetration rate of renewables by EVs or by optimizing the time-dependent carbon intensity of the national/local energy mix of energy supply caused by the uptake of energy from the grid. However, optimization for CO_2 emissions reduction is rarely explicitly considered as an objective to be optimized in an EV charging approach.

Only 3 of the 23 studies in Table 1 considered minimizing CO_2 emissions. In [68], for example, the self-consumption of solar production was maximized with optimal charging of the vehicle. Cardoso et al. [55] used average seasonal CO_2 emission values for the carbon intensity of the grid. In [74], a time series of specific CO_2 emissions was used for each kWh taken from the grid (kgCO_2/kWh). However, Fleschutz et al. [81] stated that dynamic average electricity mix emission factors can lead to inaccurate results due to the high variance of emission factors of the different fuel types. Therefore, the use of time-varying carbon emission factors instead of annual average carbon emission factors was suggested for a more accurate representation of the emission values in the energy mix. However, if the actual impact of demand response on operational carbon emissions is to be determined, Fleschutz et al. [81] suggested marginal (power plant) emission factors. Through marginal emission factors, the load change is assessed with the carbon intensity of the demand of the marginal power plant for each time step.

5. Battery Degradation

There are several types of batteries for EVs, e.g., nickel-metal hydride (Ni-MH) batteries, lead-acid batteries, and sodium–nickel chloride batteries, but most are based on lithium-ion technology. Recent literature reviews [77,82,83] regarding lithium-ion batteries show that lithium-ion batteries are currently and will be the preferred option for modern EVs and PHEVs because they offer several advantages. These include better charging efficiency, higher number of charging cycles, remarkable high-current capability, high specific energy and power, low memory effect, and, most importantly, the continuous decrease in initial cost and advanced manufacturing technology. As an example, Ni-MH batteries have been almost completely replaced by lithium batteries in EVs and PHEVs. The disadvantage of lithium-ion batteries is mainly high operating temperatures, which can have a negative impact on their energetic performance and, in the context of battery degradation, on their lifetime [84].

The main lithium-ion battery types used for EV applications are as follows: lithium ion manganese oxide (LMO), lithium iron phosphate (LFP), lithium nickel manganese cobalt oxide (NMC), and lithium nickel cobalt aluminum oxides (NCA) [85]. In particular, NMC and NCA batteries seem to be the best for powering EVs [86]. Moreover, according to Guo et al. [87], NMC and NCA are preferred as the choice for electric vehicle power supply due to their inherent characteristics, such as higher power and energy density and low cost.

Nevertheless, for the use in EVs, the life cycle and safety characteristics of lithium-ion batteries should be more important than capacity [85]. In [88], the performance parameters of lithium-ion battery cells were compared. The results show that LFP batteries in particular, despite the high cost and low energy and power density, have a long cycle and calendar life with high safety, favoring the integration of EVs in the V2G context.

Since the focus of this paper is not solely on battery degradation in the context of EVs, a complete discussion on the battery structure and chemical functionality is beyond the scope of this paper; interested readers are directed to [78,89]. In this paper, factors leading to a non-linear and complex aging process of lithium-ion batteries are considered. Battery degradation has a direct impact on the lifetime of a battery and, in addition to reversible self-discharge, usually has an irreversible character. One consequence of the aging process is the increase in internal resistance and the decrease in capacity, leading to a decrease in performance over time.

A distinction is made between calendar (chemical) and cyclic (mechanical) aging. Calendrical aging occurs over time during storage, independent of battery usage. Cyclic aging refers to the effects caused by cycling due to the use of the battery. Both processes lead to a decrease in capacity and thus to a reduction in the remaining useful life [90]. When the available capacity or maximum power of the battery is reduced by 20% (sometimes 30%) of its original value, it is generally considered that the battery has reached its end of life (EOL). This corresponds to a state of health (SOH) of 80%. The SOH gives an indication of the progress of battery degradation, measured as a percentage. It is defined as the quotient of the current maximum capacity at full charge and the original maximum capacity.

5.1. Battery Degradation Models

Various types of models exist in the literature for estimating battery degradation. Although other classifications are possible, battery degradation models can be divided into two main categories, namely empirical [91–94] or semi-empirical models [95–100] and physically based statistical/electrochemical models [101–106]. Such models attempt to describe the dependence of battery capacity and resistance on various aging factors. Both electrochemical and empirical approaches have their advantages and disadvantages. Electrochemical models mainly refer to the reaction mechanism inside the battery and thus rely heavily on fundamental theory to understand the detailed internal electrochemical reaction process and reaction intensity of degradation inside the battery [107]. They derive the simulated behavior from known equations that represent the physical behavior [89]. Due to the complexity and increased computational costs of electrochemical models, the question of practicality in smart grid studies arises. The resulting low computational efficiency and the presence of numerous input parameters represent the main drawback of electrochemical models [108]. To address complexity, semi-empirical and empirical models combine theoretical foundations with experimental results to gradually assign appropriate equations and parameters to the models to achieve the best fit to experimental data.

Table 2 shows current battery degradation models from the literature, characterizes them by type of degradation model and battery, by type of degradation (calendar or cycling degradation), and by factors analyzed, and shows the main highlights of the studies examined. The focus in the examination of the degradation models was placed on cycling degradation, as this is crucial in the context of V2G simulation. The EV experiences calendar degradation regardless of V2G use, and since it is the additional degradation caused by V2G use that is of most interest, V2G studies usually leave calendar degradation out of the equation. Moreover, only a few studies simulate longer periods where calendar degradation is an essential factor of overall battery degradation as, for example, in [109]. Here, the authors conducted the simulation assuming a daily charge/discharge, a cell temperature of 25 °C, and a DOD of 10%. The results show that the SOC condition has a significant impact on degradation costs. If the SOC could be maintained at a low level, the overall costs with a DR strategy could be reduced noticeably. Under these assumptions, calendar degradation was found to be several times higher than cyclical degradation. However, periods of several years were considered.

Most of the papers reviewed as well as many studies in the literature regarding battery degradation models use empirical or semi-empirical models due to their ease of use. According to the studies reviewed, empirical and semi-empirical models are the most suitable candidates in the context of battery degradation in smart grid studies for EVs. While they are not as robust as physical models, their ease of integration into existing V2G models and sufficient accuracy make them applicable to many EV battery degradation scenarios. Therefore, empirical models are often used in battery management systems due to their speed, memory space, and numerical convergence [89]. It can also be seen from Table 2 that the parameters of most models are for lithium-iron-phosphate batteries, which are of greatest interest for EVs. The model output of most studies is the capacity loss of the (lithium) battery. Only a few studies investigated other outputs in this context, such as a prediction of battery life or a maximum number of cycles of the EVs. In the literature, a range between 1000 and 3000 cycles is considered realistic [77]. The most frequently investigated factors leading to the model outputs are: C-rate, SOC, battery temperature, DOD, and time (especially for calendar degradation).

Table 2. Battery degradation models.

Study	Battery Type	Degradation Model	Calendar Life	Cycle Life	Analyzed Factors	Model Output	Highlights
Yang et al. (2019) [101]	NCA (18,650-type cells)	Electrochemical-thermal-mechanical model	No	Yes	C-Rate, Temperature	Battery capacity loss	Lower and higher ambient temperatures accelerate capacity degradation. High C-rates can increase active material loss significantly. Capacity loss is, in the initial stage of aging, nearly linear but starts to accelerate after performing hundreds of cycles.
Friesen et al. (2017) [102]	NCM (18,650-type cells)	Electrochemical model	No	Yes	Temperature	Effect of different aging temperatures	Slight temperature fluctuations can result in a propagation of electrochemical reactions.
Motapon et al. (2020) [103]	LFP (26,650 type cells), NCM (18,650-type cells)	Physical model	No	Yes	DOD, Temperature, C-Rate	Impact on battery capacity	A generic cycle life model to represent the impact of cycle life drivers.
Wang et al. (2016) [95]	NCM (18,650 type cells)	Semi-empirical	Yes	Yes	Temperature, C-Rate, Time	Battery capacity loss	Minor impacts from infrequent V2G services on battery life. Frequency control and peak load reduction do not result in significant degradation.
Petit et al. (2016) [91]	LFP (A123), NCA (Saft VL6P)	Empirical model	Yes	Yes	SOC, Temperature, Current	Battery capacity loss	Major differences between both battery types (LFP and NCA).
Omar et al. (2014) [96]	LFP (battery cells)	Semi-empirical	No	Yes	Temperature, C-Rate, DOD	Maximum number of cycles before EOL (80%)	Operating temperature has a great impact on the service life of the battery. High C-rates have a harmful impact on the performance of the battery.
Ouyang et al. (2016) [104]	LFP, LMO+NCM (battery cells)	Mechanistic and prognostic model	No	Yes	C-Rate, Temperature	Battery capacity loss	The lifetime of lithium-ion batteries is very temperature dependent; high temperatures can accelerate the degradation significantly. Commercially available batteries with an LFP cathode degraded significantly slower than batteries with a mixed cathode material (LMO + NCM) under the same conditions. Higher C-rates or SOCs result in faster losses of lithium inventory.
Li et al. (2018) [105]	LFP (A123 batteries)	Electrochemical model	Yes	Yes	Current, Temperature	Battery capacity loss	Capacity losses strongly depend on C-rates and SOCs. SOC and temperature are the most significant parameters affecting storage conditions. During the cycle, the total energy throughput, the C-rate, and the temperature have the most influence on the battery capacity loss.
Uddin et al. (2017) [92]	NCA (18,650 type cells)	Empirical model	Yes	Yes	Temperature, SOC, C-Rate	Battery capacity loss	Smart grids can extend EV battery life (compared to cases without V2G).
Dubarry et al. (2017) [93]	NCA (NCR18650B battery cells)	Empirical model	Yes	Yes	Time, SOC, Temperature	Battery capacity loss	Capacity loss is increased by 75% and resistance by 10% with twice-daily V2G. V2G strategies had a negative impact on cell efficiency.The influence of SOC at higher temperatures is more significant.
Chen et al. (2021) [97]	Ni-MH (battery cells)	Semi-empirical model	No	Yes	C-Rate, Temperature, DOD	Battery capacity loss	DOD has the greatest impact on battery life.
Johnen et al. (2021) [106]	NCM, LFP (battery cells)	Statistical model	No	Yes	C-Rate, SOC	Predict capacity behavior of battery	Useful model for batteries in second-life settings.
Olmos et al. (2021) [94]	NMC, LFP (battery cells)	Empirical model	No	Yes	Temperature, C-Rate, DOD, SOC	SOH evolution/relations between stress factors and capacity loss	NMC: DOD and temperature accelerate battery degradation the most. LFP: Discharge C-rate is the most limiting degradation stress factor; low degradation dependency on DOD.
Wang et al. (2014) [98]	NCM + LMO (18,650 type cells)	Semi-empirical model	Yes	Yes	Temperature, C-Rate, DOD	Predict battery life for various temperatures and rates	High temperatures lead to a higher loss of calendar life, and low temperatures and high C-rates lead to a higher loss of cycle life.
Sarasketa-Zabala et al. (2016) [99]	LFP (26,650-type cells)	Semi-empirical model	Yes	Yes	SOC, Temperature, DOD, C-Rate	Lifetime prognosis	The effects of calendar and cyclic degradation can be used in combination for degradation prediction under dynamic and complex operating conditions.
Cordoba-Arenas et al. 2015 [100]	NMC+LMO (battery pouch cells)	Semi-empirical model	No	Yes	SOC, Temperature, C-Rate	Predicting battery cycle life	Degradation model to predict battery life under realistic EV scenarios.

NCA = lithium nickel cobalt aluminum oxide; NCM/NMC = lithium nickel cobalt manganese oxide; LFP = lithium iron phosphate battery; LMO = lithium ion manganese oxide; NiMH = nickel-metal hydride battery; EV = electric vehicle; SOC = state of charge; V2G = vehicle-to-grid; DOD = depth of discharge; EOL = end of life; SOH = state of health.

5.2. Battery Degradation Parameters

According to the current state of the art (Table 2), the main external stress factors, besides energy throughput that cause and/or exacerbate cyclic degradation of the battery, are the following:

Battery temperature: In general, temperature proves to be the most important stress factor for cyclic battery degradation, where deviations from the typical 25 °C can lead to an accelerated deterioration [89]. The literature reports that both high and low ambient temperatures [101] can accelerate the degradation of lithium-ion batteries. However, it is also shown that the relationship between temperature and SOC can have a moderate impact. For example, ref. [98] showed that the capacity loss at a low C-rate (approx. 0.5 C) is higher with increasing temperature, whereas at a higher C rate (>5 C), low and high temperatures lead to a higher capacity loss. Das also stated that temperature accelerates all chemical reactions leading to degradation [110]. Arrhenius' law is used to model the dependence of battery degradation on battery temperature. For these reasons, the influence of temperature should not be missing in a battery degradation model.

C-rate: A higher charging rate accelerates the degradation, and this effect can be amplified in combination with the other stress factors. A low C-rate leads to a low DOD. In [90], it was shown that at a high C-rate, battery degradation is high at both low and high SOCs. In [98], it was shown that capacity loss increases with higher C-rates and that this effect tends to be larger at high temperatures. Pelletier et al. [78] stated that a C-rate from one and above leads to an exponentially accelerated reduction of the cycle life of a battery.

State of charge (SOC): The literature shows that higher SOC operation accelerates battery degradation or that a low SOC contributes to reducing battery degradation. For example, ref. [105] found that the capacity loss at higher SOC is slightly higher than at low SOC at all temperatures. Accordingly, the average SOC value also influences the degradation. A higher average SOC means a faster degradation rate, and thus the timing and duration of a charge or discharge event can be adjusted to keep the average SOC low.

Depth of discharge (DOD): Some studies suggest that DOD plays a more important role in battery degradation than SOC. In [97], it was the most relevant factor affecting Ni-MH battery life. Therefore, the DOD should be reduced as much as possible, and it is best to operate in a reasonable working range (25~45 °C). Moreover, in [90], it was pointed out that the battery degrades exponentially with increasing DOD, and therefore a DOD greater than 60% should be avoided to significantly extend battery life. In [94], however, there was a huge difference in the DOD dependence on battery technologies. While for lithium nickel manganese cobalt oxides (NMC) batteries, DOD is seen as the most crucial stress factor, for lithium iron phosphate (LFP) batteries, a low impact of DOD can be seen as an essential advantage.

6. Optimization Scenarios in Smart Grids Considering Battery Degradation

Several studies have addressed smart grid optimization scenarios that take battery degradation into account. The optimization problems investigated can be divided into two groups: optimization problems with only one objective (single-objective optimization) and multi-objective optimization, in which the simultaneous optimization of individual objectives is allowed. Here, individual objectives can be weighted and then evaluated regarding their importance for the overall problem in a Pareto analysis. In total, 19 research findings related to single- or multi-objective optimization considering battery degradation in smart grids are presented in Table 3.

For this purpose, the objectives, the integration of battery degradation, the components of the power system (EV, BESS, and RES), the time horizon, and the time resolution of the simulation were investigated. From the perspective of the objective function, most of the approaches studied have only one objective, where the cost function is minimized, or profits are maximized. Degradation costs are only integrated into the cost function. In the multi-objective optimization, profits or costs were simulated with either minimizing battery degradation, CO_2 emissions, grid net exchange, or maximizing EV energy for the building.

Another focus was placed on the applied DR program in the studies reviewed. A distinction was made regarding whether the DR program was incentive-based, price-based, or focused on stand-alone demand-side management factors such as increasing self-consumption of renewable energies. It was found that most of the studies included price-based DR programs. Only one study with incentive-based DR was identified in which a bidding system was presented.

Table 3. Optimization scenarios in smart grids considering battery degradation.

Study	Optimization Method	Objectives	Cycling Degradation	DR Program	RES	Energy Storage	Time Horizon	Time Resolution
Eldeeb et al. (2018) [111]	MOO	Maximizing revenues for PV, minimizing battery degradation	Degradation model (constant T, C-rate)	DSM	PV	BESS, BEV	1 day	10 min
Schuller et al. (2014) [112]	SOO	Minimizing cost of EV charging	Constant parameter	PB	None	BEV	7 days	15 min
Das et al. (2020) [74]	MOO	Minimizing cost, CO_2 emissions, degradation, grid net exchange	Degradation model (T, C-rate, SOC)	PB, DSM	PV	BEV	1 day	15 min
Di Giorgio et al. (2014) [56]	SOO	Minimizing cost of energy consumption and network losses	Proportional depreciation term	PB, DSM	None	BEV	6 a.m.–11 p.m.	1 h
Van der Meer et al. (2016) [113]	SOO	Minimizing total cost, increasing PV self-consumption	Constant parameter	PB, DSM	PV	BEV	1 day	15 min
Mouli et al. (2017) [65]	SOO	Minimizing total net costs	Constant degradation penalty for V2G service	PB, DSM	PV	BEV	24 h	15 min
Zhongjing et al. (2015) [58]	SOO	Minimizing the system cost	Degradation cost function (charging power)	PB	None	BEV	1 day	1 h
Iwafune and Ogimoto 2020 [109]	SOO	Minimizing total cost	Degradation model (DOD)	PB	PV	BEV	1 year	1 h
Maheshwari et al. (2020) [114]	MOO	Maximizing revenue and minimizing degradation	Degradation model (C-rate, SOC)	PB	None	BESS	1, 7 days	30 min
Miguel A. Ortega-Vazquez (2014) [115]	SOO	Minimizing total costs	Degradation model (DOD)	PB	None	BEV	1 day	15 min
Pelzer et al. (2016) [116]	SOO	Maximizing profit	Degradation model (SOC, ΔSOC, voltage)	PB	None	BESS, EV	1 year	30 min, 1 h
Xu et al. (2018) [117]	SOO	Maximizing profit	Degradation model (constant T, DOD)	PB	None	BESS	24 h	1 h
Ahmadian et al. (2018) [70]	SOO	Minimizing total cost	Degradation model (C-rate, DOD)	PB	Wind	BEV	24 h	1 h
Li et al. (2020) [73]	SOO	Minimizing the total net cost of charging vehicles	Linear degradation model (battery cost)	PB	PV	BESS, EV	24 h	5 min
Haugen et al. (2021) [118]	SOO	Minimizing the total operational costs	Degradation model (constant T, C-rate)	PB	None	BESS, EV	5 years	1, 60 min
Tchagang and Yoo (2020) [119]	MOO	Maximizing EV energy for building and minimizing battery degradation	Degradation model (SOC limits)	DSM	None	BEV	1 day (repeated for 12 years)	1 h
Terlouw et al. (2019) [120]	MOO	Minimizing the operational costs and CO_2 emissions	Linear degradation model (max energy throughput)	PB, IB, DSM	PV	BESS	1 year	1 h
Malya et al. (2021) [54]	SOO	Maximizing profit from price-based energy arbitrage	Degradation model (constant T, SOC, DOD)	PB	None	BEV	1 year	1 h
Soleimani et al. (2021) [121]	SOO	Minimizing the operational costs including battery degradation	Degradation model (DOD, energy throughput)	PB	PV	BEV	24 h	30 min

MOO = multi-objective optimization; SOO = single-objective optimization; RES = renewable energy sources; T = temperature; SOC = state of charge; PV = photovoltaic; BESS = battery energy storage system; BEV = battery electric vehicle; V2G = vehicle-to-grid; DOD = depth of discharge; IB = incentive-based DR; PB = price-based DR; DSM = demand-side management (stand-alone); min = minutes; h = hours.

6.1. Single-Objective Optimization

Few smart grid or EV charging studies in the literature deal with degradation costs as a function of several factors such as DOD, SOC, C-rate, or battery temperature. Mostly, the degradation costs are integrated into the cost function as a constant parameter or in a degradation model. For example, refs. [112,113] included battery degradation in their economic analysis as a constant parameter based on the estimated cycle life. In [122], regarding the relationship between minimum cost, feed-in tariff, and degradation, the impact of different fixed degradation rates was investigated to evaluate the profitability of V2G activities. In [65], the EV owner was compensated with a constant amount of money per kWh provided for V2G service. Some studies use a degradation model with only one influencing parameter; others establish a linear relationship via a linear approximation of variables to account for multiple parameters or to simplify the model. For example, after a linear approximation and after a simplification in the studies [109,115,117], only DOD was seen as a variable external influencing factor of cyclic battery degradation. In [73], a linear degradation was assumed, in which the battery degradation costs depended exclusively on the battery costs and the energy throughput. In [70], two influencing parameters in the battery degradation model were included in the cost function via metaheuristic optimization, namely DOD and C-rate. In the degradation model in [118], two influencing parameters (temperature and C-rate) were taken into account after linearization. Malya et al. [54] developed an arbitrage profit model to evaluate the profit that vehicle owners can make by offering their batteries. The profit is calculated based on the electricity price in the German electricity market, considering a battery degradation model from [123]. The model, which calculates cyclic and calendar degradation, takes into account the influencing factors of temperature, DOD, SOC, time, and accumulated degradation to estimate the current degradation. They estimated a profit of 662 €/EV/year for an EV and showed the potential to encourage owners of EVs to participate in V2G services. Accordingly, in the context of EV fleets in industrial or non-residential environments, instead of selling, the electricity can be used at high demand and price peaks to generate even higher revenues.

6.2. Multi-Objective Optimization

In multi-objective optimization where one objective is to minimize battery degradation, the significance is marginal if there is only one constant parameter for battery degradation. Therefore, refs. [74,111,114] modeled a battery model with at least one non-linear stress factor to simulate the non-linear behavior of battery degradation. In [111], revenues of the PV-based EV station were maximized while minimizing the degradation of the BESS with non-linear programming. For this purpose, the operating temperature is assumed to be constant in order to calculate the battery degradation as a function of the C-rate and the energy throughput. Maheshwari et al. [114] used a battery degradation model that takes into account the effects of charging rate and SOC on the degradation of a BESS. The influence of temperature on degradation is not taken into account, as the model was developed for BESS, and the storage system was housed in temperature-controlled containers. In [120], the degradation of battery performance was simplified by assuming linear degradation and applying a limit to battery use to ensure that battery life is maintained. Here, the focus was on minimizing operating costs while minimizing CO_2 emissions. In [119], the profit from selling EV energy to building owners was maximized while battery degradation of EVs was minimized. For this purpose, the battery degradation of the EVs only considered SOC as an external stress factor. For the simulation in this study, a different SOC limit was formulated for each of the five EVs.

Only the study of Das et al. [74] was found to use a battery degradation model in a multi-objective technical-economic-environmental optimization approach that represents the effects of three main stress factors (temperature, C-rate, and SOC). In this study, the battery temperature was assumed to be equal to the average daily ambient temperature and treated as an external impact factor that affects the optimization. In addition, the simultaneous optimization of four objectives was simulated: minimizing energy costs, CO_2 emissions, cyclic battery degradation of EVs, and grid net exchange.

The literature shows that numerous research studies have focused on the development and opportunities of using EVs in smart grids. However, the battery degradation of EVs has not yet been sufficiently considered. Often, as described above, strong simplifications of the degradation model are made for EVs, or only a few influencing parameters are used. Some studies use an additional BESS in the EV charging scenarios. Moreover, the integration of renewables, as can be seen in Table 3, was only considered in 9 of the 19 studies examined (8 PV, 1 wind energy), and along with this, the minimization of CO_2 was rarely considered as an optimization objective.

Another important aspect of comparison is the choice of the time step in the optimization model, as this influences the result of the optimization model. If the EV charging demand is simulated on a minute basis, the optimization will be performed on a minute basis. Haugen et al. [118] highlighted that when simulating on an hourly basis, the peak loads and the potential savings in the electricity tariff are reduced. The study showed that in short time intervals, small amounts of energy can significantly reduce the power peaks. This effect weakened with larger time steps. Furthermore, shorter time steps resulted in a more accurate EV charging demand and thus higher economic precision, while longer time steps resulted in a reduction in computation expense. The optimization models examined usually use time steps of 15, 30, or 60 min, and only a few use shorter time steps. Considering the development of fast-charging stations and the possibility to buy and sell electricity on the spot market on a 15-min basis, the use of shorter time steps shows a higher feasible economic efficiency. Comparing the time horizon, it is noticeable that many simulations consider a rather shorter period of about 24 h. Only 6 of the 19 studies from Table 3 simulated a longer period than 1 month as, for example, in [119], where simplifications were made, and the same cycle of one day was used for 12 years.

7. Discussion and Perspectives

The expansion of electric mobility offers new opportunities to minimize environmental impacts while ensuring that the needs of EV owners and stakeholders are met.

For this reason, the literature on EV charging and discharging was reviewed from the perspective of smart grids, V2G, battery degradation, and demand response. The use and profitability of V2G and smart grids are well documented in numerous research articles. This is demonstrated by issues such as energy arbitrage as in [54] to assess the profit vehicle owners could make by offering their batteries and even the positive effect of V2G on the battery as in [53] ("Beneficial V2G"). Therefore, the focus should be on the key components of smart charging and V2G of large fleets to prevent the uncoordinated and simultaneous charging of EV fleets due to grid impacts and economic reasons. The most challenging aspect for researchers is the appropriate integration of EV fleets to ensure grid stability while minimizing battery degradation of EVs and compensating for the economic losses of vehicle owners.

As part of this, many studies simulate the economic and environmental interests of EV owners under battery degradation and often consider renewable energy generation. Empirical, semi-empirical, and physics-based statistical/electrochemical models have been used in modeling battery degradation. Thus, degradation modeling of EV charging scenarios has largely focused on empirical or semi-empirical modeling over physical modeling. Influential battery degradation parameters regarding cycling degradation (battery temperature, C-rate, DOD, SOC) for EV charging scenarios in the literature were highlighted. It was shown that the non-linear behavior of battery degradation, especially in EV charging scenarios, is not fully taken into account. Adapted battery degradation models are needed for different battery types, as the current battery technologies (NMC, NCA, and LFP) have individual strengths and weaknesses. A detailed overview can be found in [85,88].

In the course of multi-objective optimization of EV charging scenarios considering battery degradation and the trade-off of more than two objectives (e.g., energy cost, CO_2

emissions, compensation of vehicle owners, and battery degradation), there is a clear lack of studies to identify future potentials. Here, the conflicting goals of the different stakeholders should be optimized in a multi-criteria approach. Thus, in an optimal trade-off scenario, where EV owners that make a net profit by providing their EVs may encourage other EV owners to participate in V2G scenarios or even encourage ICEV owners to adopt an EV. Moreover, the social question should be answered: when and under which circumstances would an EV owner allow another stakeholder (e.g., the company where they are employed) to use their battery?

To the best of the authors' knowledge, there are no such multi-objective optimization of EV charging scenarios in the industrial setting that adequately considers battery degradation and demand response. The main research gaps identified in the current literature can be summarized as follows:

- Battery temperature, which is considered an important loading factor, has generally received little attention. Either the temperature was considered constant or simplifications were made assuming that the battery temperature corresponds to the average daily ambient temperature.
- The minimization as well as the trade-off between CO_2 emissions reduction and battery degradation, in contrast to the minimization of system costs, was not sufficiently proven.
- There is a lack of studies that comprehensively consider battery degradation in EV charging scenarios and balance it with financial compensation for EV owners (especially in the non-residential setting). This trade-off between EV owners and companies regarding the benefits to the company and the balance between battery degradation and profit in the form of subsidized or free charging electricity for the EV owner is not appropriately quantified in the literature.
- There are no studies that have investigated non-residential demand response in smart grids, taking into account larger EV fleets and appropriate battery degradation to show economic and environmental perspectives.

The limitations of this study involve the consideration of battery degradation, which should be further explored. In Table 2, all degradation models refer to test cells or batteries that have been partially interconnected to mimic a battery in an EV. Therefore, analysis of a real EV over a longer period of time would be extremely interesting. Current studies on EV battery use and degradation often refer to standardized data (driving patterns, operating times, driving cycles), and thus real-world degradation in EVs could be under- or overestimated.

8. Conclusions

The literature on EV battery use and modeling for non-residential EV charging was reviewed in terms of battery degradation, demand response, and optimization in single- and multi-objective simulations. From the literature review, it appears that further studies focusing on multi-objective optimizations in the non-residential setting in the field of EV fleet charging are needed internationally. In addition, future research studies should consider the following three aspects to ensure best practices:

1. When considering battery degradation, battery degradation models should be used that take into account several external influencing factors, in particular battery temperature, C-rate, and SOC or DOD. Regarding battery temperature, as an important influencing factor, more accurate assumptions than average daily ambient temperatures should be used, since battery temperature usually increases with time of use.
2. Multi-objective optimizations should consider the trade-off between several objectives, namely energy costs, CO_2 emissions, battery degradation, and compensating vehicle owners for using their batteries in non-residential scenarios, given the economic and environmental drivers. In this context, each objective should be compared with an appropriate weighting, e.g., using a game-theoretic analysis to make profitable decisions.

3. Demand response should be expanded in terms of workplace EV charging. To this end, scenarios in non-residential, i.e., industrial and commercial, sectors should be further investigated to find the economic and environmental profitability as well as the willingness of employees to offer their batteries.

Addressing these three aspects will help future-proof studies in the area of EV battery utilization in non-residential demand response and ensure more robust analyses that can be compared to those of future related studies. In addition, a better understanding of battery degradation through statistical analysis and empirical modeling will lead to higher reliability of predictions regarding profitability.

An interesting area of future research would be the different characteristics of lithium batteries in terms of degradation in EVs during driving and cycle or calendar life. Degradation models could be developed based on the analysis of EV batteries to show potential correlations in the degradation of battery types between driving degradation and cycle/calendar degradation. In addition, the motivation for people to participate in V2G contracts in an industrial setting could be investigated with real-life user studies.

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Nomenclature

AB	aggregated battery
BESS	battery energy storage system
BEV	battery electric vehicle
DOD	depth of discharge
DR	demand response
EOL	end of life
EV	electric vehicle
ICEV	internal combustion engine vehicle
LFP	lithium iron phosphate
LMO	lithium ion manganese oxide
MOO	multi-objective optimization
NCA	lithium nickel cobalt aluminum oxide
NMC	lithium nickel manganese cobalt oxide
NI-MH	nickel–metal hydride
PHEV	plug-in hybrid electric vehicle
PV	photovoltaic
RES	renewable energy sources
RTP	real-time pricing
SOC	state of charge
SOH	state of health
SOO	single-objective optimization
V2G	vehicle-to-grid
XB	individual batteries

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