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Review

A Review of Bidirectional Charging Grid Support Applications and Battery Degradation Considerations

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Abstract: Electric vehicles (EVs) are crucial in mitigating global emissions by replacing internal combustion engines. The capacity of EV batteries, coupled with their charging infrastructure, offers the added advantage of supplying flexible demand capacity and providing demand response benefits to the power grid, which is essential as overall demand increases. EVs ready for vehicle-to-everything (V2X) applications and chargers that support them enhance this flexibility by allowing for varied storage applications. However, to fully harness these benefits, it is vital to consider EV drivers' charging habits and optimize the charging and discharging controls to minimize battery life impact. This study examines various V2X applications in North America and their effects on battery longevity, considering EV charging patterns. Additionally, it investigates advanced aging-aware optimization algorithms for managing bidirectional charging.

Keywords: bidirectional charging; V2X; battery degradation; grid demand

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Citation: Adegbohun, F.; von Jouanne, A.; Agamloh, E.; Yokochi, A. A Review of Bidirectional Charging Grid Support Applications and Battery Degradation Considerations. *Energies* **2024**, *17*, 1320. https://doi.org/10.3390/en17061320

Academic Editor: Adel Merabet

Received: 11 February 2024
Revised: 6 March 2024
Accepted: 7 March 2024
Published: 9 March 2024

1. Introduction

From 2023 to 2030, it is projected that the U.S. will need to ramp up its power generation capacity significantly, adding over 200 GW to meet peak demand [1]. This figure could almost double if the U.S. aims for 100% clean electricity by 2035 [1]. Such growth scenarios will introduce an unparalleled mix of renewable energy sources reliant on weather, leading to a more fluctuating electricity supply and a surge in the need for transmission capacity. Currently, transmission interconnection backlogs are a growing concern, with average wait times extending to about five years [2], which could impact resource adequacy.

Virtual power plants (VPPs) represent a modern concept in the field of energy management and power generation that aggregates and remotely controls a diverse array of energy assets, such as solar panels, wind turbines, energy storage systems, demand response programs, and other distributed energy resources, and which are likely geographically dispersed and may belong to different stakeholders. VPPs are mainly enabled by robust communication networks enabling seamless communication between a central aggregation software platform and the distributed energy resources, to direct real-time monitoring, control, and coordination of the assets [3–6].

Virtual power plants are a low-cost, viable solution to enhance resource adequacy. They offer more than just economic benefits; VPPs enhance resilience, may cut down on greenhouse gas emissions and air pollution, alleviate transmission and distribution (T&D) congestion, empower communities, and are adaptable to the changing needs of the grid [7]. The potential distributed energy resource (DER) capacity joining VPPs is on a rapid rise, with EVs constituting a significant portion of this growth due to their highly adaptable demand [8,9]. Estimates indicate that between 2025 and 2030, the grid will integrate 20–90 GW of demand capacity/response from EV charging infrastructure and 300–540 GWh of storage capacity from EV batteries. When demand capacity increases, the max power the grid can deliver at any point in time and demand response are modified based on current or predicted grid conditions. This lays an emphasis on the shift towards electric vehicles (EVs) and its pivotal multi-faceted impact on the global push to slash carbon emissions. Nonetheless, incorporating electric vehicles (EVs) as dynamic energy storage systems introduces new operational complications, such as coordinating the driving and charging patterns of EV drivers with vehicle-to-everything (V2X) applications, where X represents the grid or a microgrid (V2G or V2M), other vehicles (V2V), homes and buildings (V2H and V2B), or generic load (V2L) applications, which require use of aging-aware controls to maximize battery longevity [10].

Considering the charging patterns, trip duration, parking duration, charger type and charging location (e.g., office, home, or public charging facility), vehicle type (e.g., heavy or light duty commercial, or passenger) are important in examining the potential value addition of EVs and charging infrastructure in a VPP. Comprehensive studies of the impact of EV driving patterns on V2G applications have been presented in literature [11]. The collective research across these studies highlights the potential of V2G technology to enhance power grid stability and efficiency, driven by optimized EV charging and discharging strategies that consider user behavior, driving patterns, and economic benefits. Additionally, these studies underscore the importance of integrating EV user preferences and stochastic factors into V2G systems to maximize the reliability, cost-effectiveness, and environmental benefits of EV integration into power grids [11–20].

This paper presents a conceptual assessment of the multifaceted role of EVs in enhancing grid stability and flexibility, particularly through bidirectional charging and V2X applications. The paper offers a comprehensive analysis that not only examines the technical capabilities and real-world applications of bidirectional EV charging but also delves into the pivotal impact of EV drivers' charging behaviors on battery life and grid demand. Our study is significant for its in-depth assessment of the integration of EVs as dynamic components in VPPs, addressing the challenges and opportunities they present in the context of an increasingly renewable-dependent energy landscape. The paper is intended for a diverse audience encompassing various key players in the energy sector, particularly those involved with VPPs and bidirectional battery operations.

The following sections of the paper start by analyzing how EV batteries contribute to meeting grid demand, emphasizing their role in flexible demand capacity. The paper then explores the capabilities and diverse applications of bidirectional charging, backed by a survey of its real-world implementations. We then provide a deep dive into the degradation mechanisms of EV batteries highlighting the factors that exacerbate them. Furthermore, we delve into the realm of V2X applications, assessing their impact on battery life and considering EV charging patterns in this broader context. The paper also introduces and evaluates aging-aware optimization algorithms for bidirectional charging, a novel approach in extending battery life while ensuring efficient grid operation. We conclude the paper by summarizing the key takeaways and outlines recommendations for future research and real-world implementation.

2. EV Batteries, EV Chargers, and Grid Demand

EV nameplate demand capacity additions are expected to add 20 GW to the US electrical load by 2025 and 90 GW by 2030 [8,21,22]. Similarly, nameplate EV storage capacity additions are expected to soar to 305 GWh and 540 GWh in 2025 and 2030, respectively as illustrated in Figure 1, representing a total DER capacity investment in EVs that is estimated to be between $290–505 billion per year (2025–2030) [7]. This growth coincides with expected additions to electrification of space and water heating using heat pumps, and some expected asset retirements, and is poised to drive demand growth needs of ~200 GW, which is between 10–20% of current peaks [1,7]. The grid already faces a number of resiliency challenges, with more frequent blackouts occurring due to weather related events in states such as Texas and California [23]. Demand response management devices that are connected such as smart thermostats and smart water heaters driven by energy efficient heat pumps participate as VPPs and can help achieve significant peak reductions [24]. Similarly, early demonstrations of V2G based VPPs show the promise that V2G technology can play a significant role in reducing peak demand as well as times when they may be crucial to grid resiliency [25–27]. Estimated savings for U.S. utilities in capacity investment for new peaker plants, transmission and distribution upgrades could be between USD 15 to USD 35 billion/year, when these investments are deferred and VPPs are widely adopted (ignoring the additional societal benefits like emissions reduction and resiliency) [1]. Multiple stakeholders—including bulk power system operators, distribution system operators, VPP platform operators, and electricity consumers—play different key roles in the value chain of making VPPs a reality.

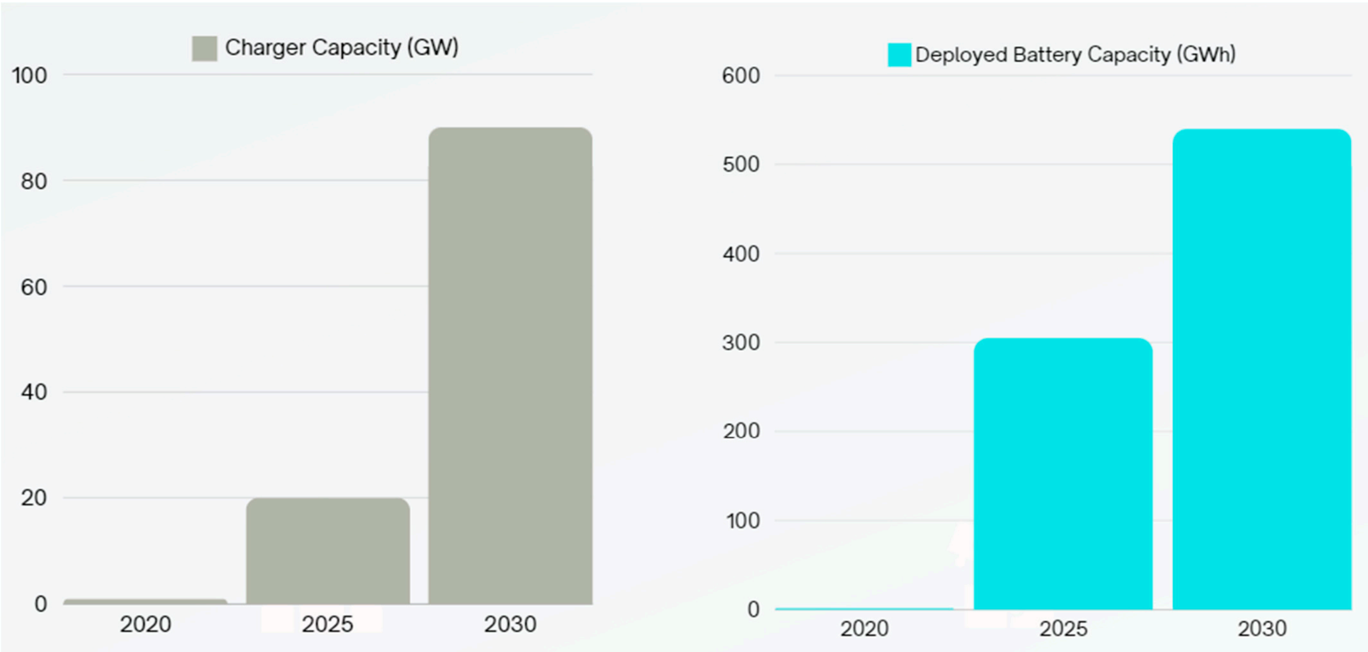

Figure 1. Nameplate EV charger and EV battery forecast (2025–2030) [7].

Figure 2 illustrates a diagram of the interactions between each of the stakeholders within a VPP [7]. The figure illustrates the end-to-end integration of virtual power plant (VPP) systems, showcasing a seamless interaction between various stakeholders and components. At its core is the VPP operator, equipped with IoT data analytics and a dispatch platform, orchestrating the entire process. This operator is interconnected with the bulk power system operator, responsible for the macro-level grid balance, and the local distribution system operator for more granular grid operating conditions. Electricity customers, ranging from residential to industrial, form the network's endpoints with devices like smart water heaters, bidirectional and unidirectional EV chargers, and smart thermostats. These components work in unison, allowing the VPP to efficiently manage energy demand and supply, ensuring grid stability and optimizing the use of distributed energy resources [7]. The VPP's sophisticated communication and control systems facilitate this integration.

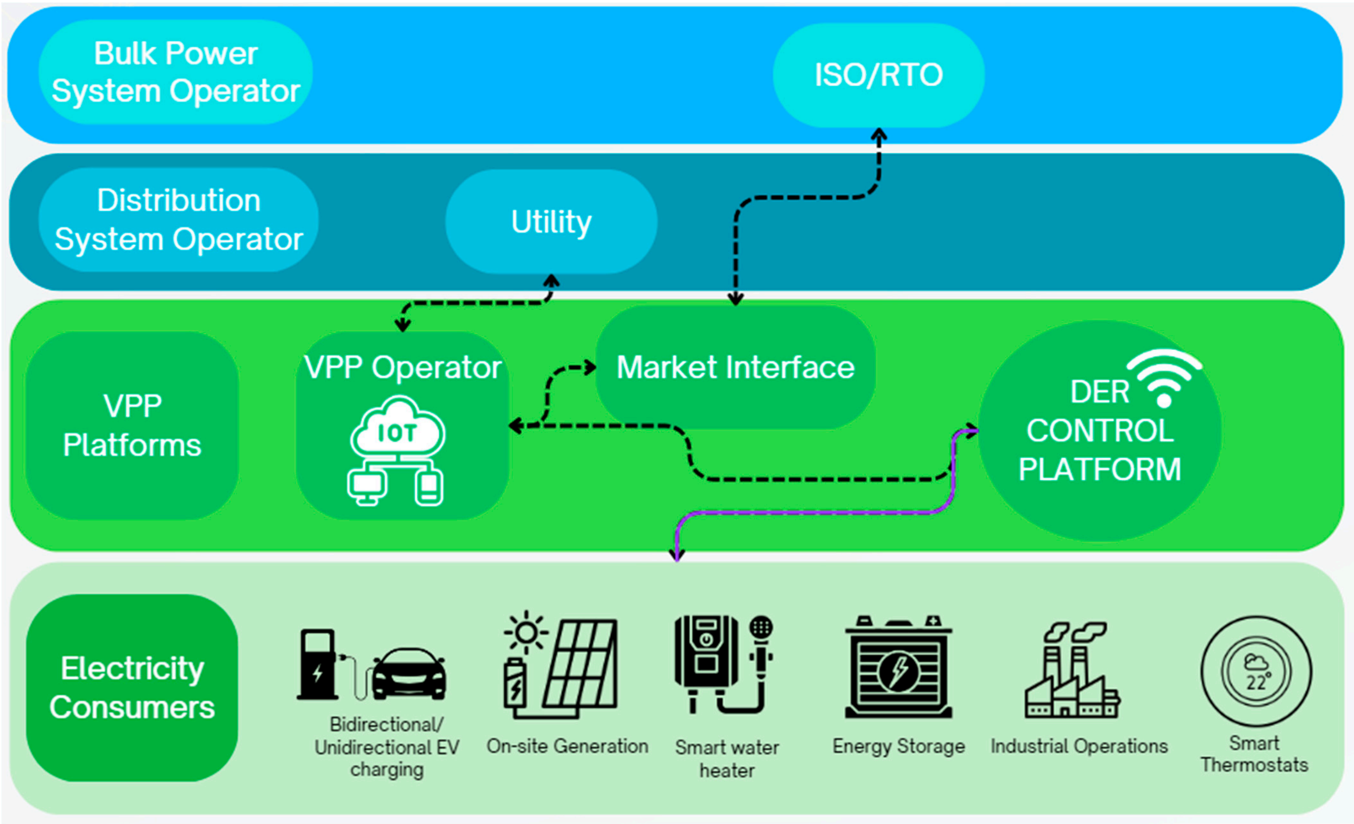

Figure 2. VPP operational model [7].

Virtual Power Plants and EV Charging Cost Reduction

The economic model of VPPs is influenced by the composition of distributed energy resources (DERs) and their operational strategies. At their core, however, they share similar cost and revenue structures. On the cost side, these include the expenses associated with establishing and operating DER management systems, which encompass project implementation, administrative tasks, and the management of payments. Additionally, costs arise from acquiring participants or customers, which may involve marketing, consumer education, recruitment efforts, and the provision of rebates and subsidies. Incentives for participants also form a part of the costs, which could be one-time payments, recurring payments, or payments based on the amount of kWh produced. On the revenue side, VPPs earn income through payments for every MWh delivered, typically received from utilities via independent system operators (ISOs) [7]. They also generate revenue through capacity payments for each MW of energy provided by the VPP collective, as well as from ancillary services like frequency regulation and ramping. Furthermore, VPPs can benefit from payments related to the avoidance of infrastructure upgrades, contributing to their overall financial viability.

EVs present both a challenge and an opportunity for grid management. VPPs can mitigate the challenges through:

Demand Response Integration: By integrating EVs into demand response programs, VPPs can shift EV charging to off-peak hours, reducing strain on the grid and lowering charging costs due to off-peak rates.

Dynamic Pricing Models: Utilizing dynamic pricing models, VPPs can encourage EV owners to charge during periods of low demand or high renewable generation, thus optimizing charging costs.

Renewable Energy Synchronization: By synchronizing EV charging with periods of high renewable energy generation (e.g., solar during midday), VPPs can further reduce the marginal cost of charging.

VPPs can actively participate in electricity markets, offering several services that are particularly relevant in the context of EV charging:

Energy Arbitrage: VPPs can leverage price differentials in the electricity market, storing energy in EV batteries when prices are low and releasing it back to the grid when prices are high.

Ancillary Services: EV batteries in a VPP can provide frequency regulation and voltage support, creating revenue streams for VPP operators and EV owners.

Capacity Market Participation: By aggregating EVs, VPPs can bid into capacity markets, providing a guaranteed energy reserve, thus opening a revenue stream that offsets EV charging infrastructure costs.

3. Bidirectional Charging: Capabilities and Applications

The advent of bidirectional charging capabilities in EVs has opened new frontiers in energy management, with significant implications for grid stability, renewable energy integration, and consumer convenience. This section explores the range of bidirectional charging technologies, focusing on non-exporting and exporting capabilities, and the various sub-categories within V2X applications.

3.1. Non-Exporting Bidirectional Charging

Non-exporting bidirectional charging involves EVs supplying power to homes or specific loads behind the meter rather than feeding back into the grid. This is usually described as vehicle-to-load (V2L) or vehicle-to-building (V2B). This application is crucial during power outages or for off-grid power solutions. There are two primary topologies in non-exporting bidirectional charging: systems that require an external electric vehicle supply equipment (EVSE) and those that rely solely on the vehicle's onboard charging equipment. The former, often equipped with smart capabilities, can be programmed to supply power during peak demand or outages, as noted by Heydari-Doostabad et al. [28]. The latter, on the other hand, leverages the inbuilt inverter capability of the vehicle to supply power directly to home appliances or other loads, a concept explored by Khan et al. [29] and Chang et al. [30].

3.2. Exporting Bidirectional Charging

In exporting bidirectional charging, EVs can send electricity back to grid-tied loads. This functionality is integral to Vehicle-to-Grid (V2G) systems, facilitating energy flow from EVs to the power grid, thereby aiding in demand response management and grid stabilization. Tang et al. [31] highlight how this can optimize battery charging performance while accommodating grid needs.

Figure 3 describes common bidirectional charging system configurations and their interconnection mechanisms. Depending on whether a bidirectional charging system is exporting or non-exporting, it will vary in their permitting and thus their scale of deployment [32]. Exporting scenarios where the system is grid tied will typically involve more stringent constraints that require at least permission from the utility and oftentimes interconnection studies to take place, in order for the interconnection to be approved and for the system to begin operational [32].

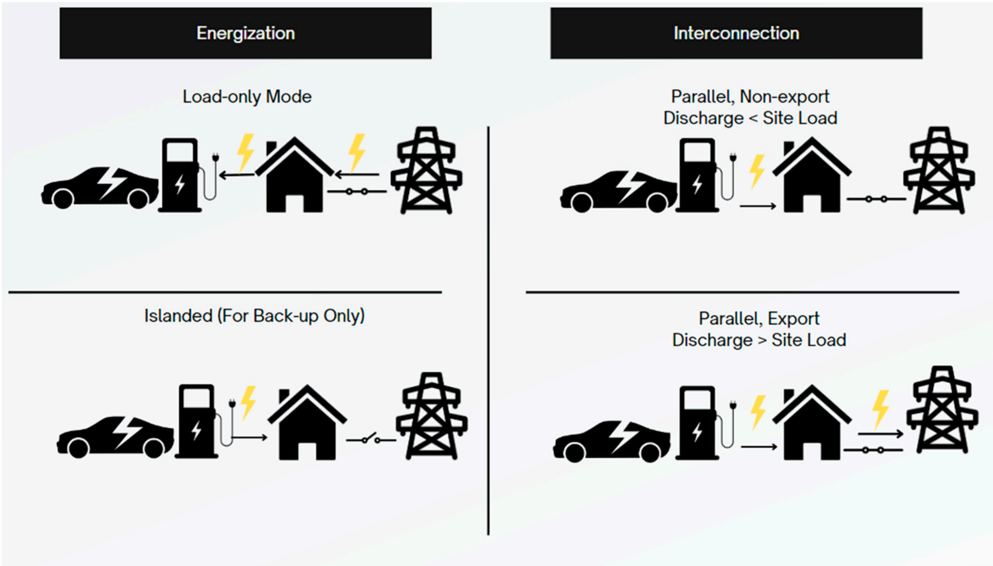

Figure 3. Common V2X bidirectional charging system configurations, adapted from [32].

3.3. V2X Applications

3.3.1. Vehicle-to-Grid (V2G)

V2G technology enables EVs to interact with the power grid, providing ancillary services like frequency regulation. This interaction not only stabilizes the grid but also opens revenue streams for EV owners. EVs in V2G applications can participate in various grid-support services:

Frequency Regulation: EVs help stabilize the grid frequency by quickly responding to grid demand fluctuations. This requires EVs to have fast-response charging systems capable of rapidly adjusting power output. Amamra et al. [19] illustrate an optimized bidirectional V2G operation, which uses a fleet of EVs to participate in frequency and voltage regulation services, thereby reducing EV ownership charging costs.

Energy Storage for Renewable Integration: EV batteries store excess renewable energy, particularly from intermittent sources like solar and wind, reducing the need for traditional energy storage systems. This application requires EVs to have a charging schedule aligned with renewable generation patterns, Ota et al. [33] propose an autonomous distributed V2G control scheme where grid-connected EVs supply distributed spinning reserve according to frequency deviation, which signals supply and demand imbalance in the power grid. This scheme addresses the need for EV batteries to store excess renewable energy, particularly from intermittent sources like solar and wind, and requires EVs to have a charging schedule aligned with renewable generation patterns, emphasizing the role of EVs in balancing power imbalances caused by intermittent renewable energy sources.

Reducing Grid Congestion and TaD Upgrade Cost Deferrals: By absorbing or supplying power, EVs can alleviate grid congestion during peak hours, delaying the need for transmission and distribution (TaD) infrastructure upgrades. Gowda et al. [34] investigate the potential of EVs with V2G capability to provide TaD deferral and congestion relief services. An analysis of virtual power plants by the Brattle group [1] estimated that the required distribution grid investments needed to meet future electrification and decarbonization demand may be up to USD 50 billion by 2035 but could be as much as ~70% lower if measures are taken to manage flexible demand from DERs including EVs.

Different duty cycles are expected depending on the application. For frequency regulation, EVs undergo frequent, short-duration charging and discharging cycles. For energy storage, the charging cycle aligns with renewable generation patterns, often mid-day for solar energy.

3.3.2. Vehicle-to-Microgrid (V2M)

In V2M applications, EVs interface with localized grid systems like microgrids. The infrastructure typically includes renewable energy sources, storage systems, and advanced metering. Kaur et al. [35,36] discuss the integration of renewable energy sources in microgrids, emphasizing the role of energy storage, including V2G technology, to balance demand and supply. It highlights the significance of electric vehicle (EV) batteries as additional storage in microgrids, providing services such as load shifting and frequency variation management. The model presented includes solar and wind energy sources along with an electrical vehicle aggregator in an integrated environment, illustrating the feasibility and benefits of V2G in microgrids.

3.3.3. Vehicle-to-Home/Building (V2H/V2B)

V2H/V2B applications involve EVs supplying power to residential or commercial buildings. The type of building dictates the application, with residential buildings focusing more on backup power and peak shaving, while commercial buildings leverage load shifting to benefit from time-of-use tariffs. The versatility of V2H/V2B applications is highlighted by Shima et al., including proposing of energy management algorithms for V2B/V2H applications and the battery degradation concerns for V2B [37]. Higashitani et al. [38] evaluate the profitability and optimal configuration of vehicle-to-home (V2H) technology for residential energy systems, considering various household types and storage options. It optimizes residential energy systems under scenarios with different electricity demand profiles, automobile usage patterns, and available areas for PV installation. The study finds that V2H systems should generally be installed instead of stationary batteries, especially for households with short EV absence times, large available areas for PV installation, and high electricity demand. V2H demonstrates superior energy independence and energy-saving effects for households whose annual PV generation exceeds their yearly electricity demand.

3.3.4. Other V2X Applications

Vehicle-to-Load (V2L): This application involves using EVs as mobile power sources, particularly for outdoor events or remote locations where grid power is unavailable. The Ford F-150 Lightning, equipped with 9.6 kW of onboard power, exemplifies the innovative use of electric vehicles in V2L applications. It offers up to 11 power outlets with both 120 V and 240 V capabilities, making it a versatile mobile power source suitable for diverse scenarios [39].

Vehicle-to-Vehicle (V2V): In V2V, one EV can charge another, which is particularly useful in emergency situations or when conventional charging infrastructure is unavailable. The versatility of V2V applications is highlighted by Ucer et al. [40], who propose a bidirectional EV-to-EV charge-sharing solution for flexible grid integration.

Figure 4 is a visual illustration of the different V2X configurations and capabilities, highlighting the expanding capabilities of bidirectional charging in EVs and demonstrating their potential as dynamic tools for energy management. As these technologies evolve, they promise to play an increasingly integral role in creating a sustainable, resilient, and efficient energy ecosystem.

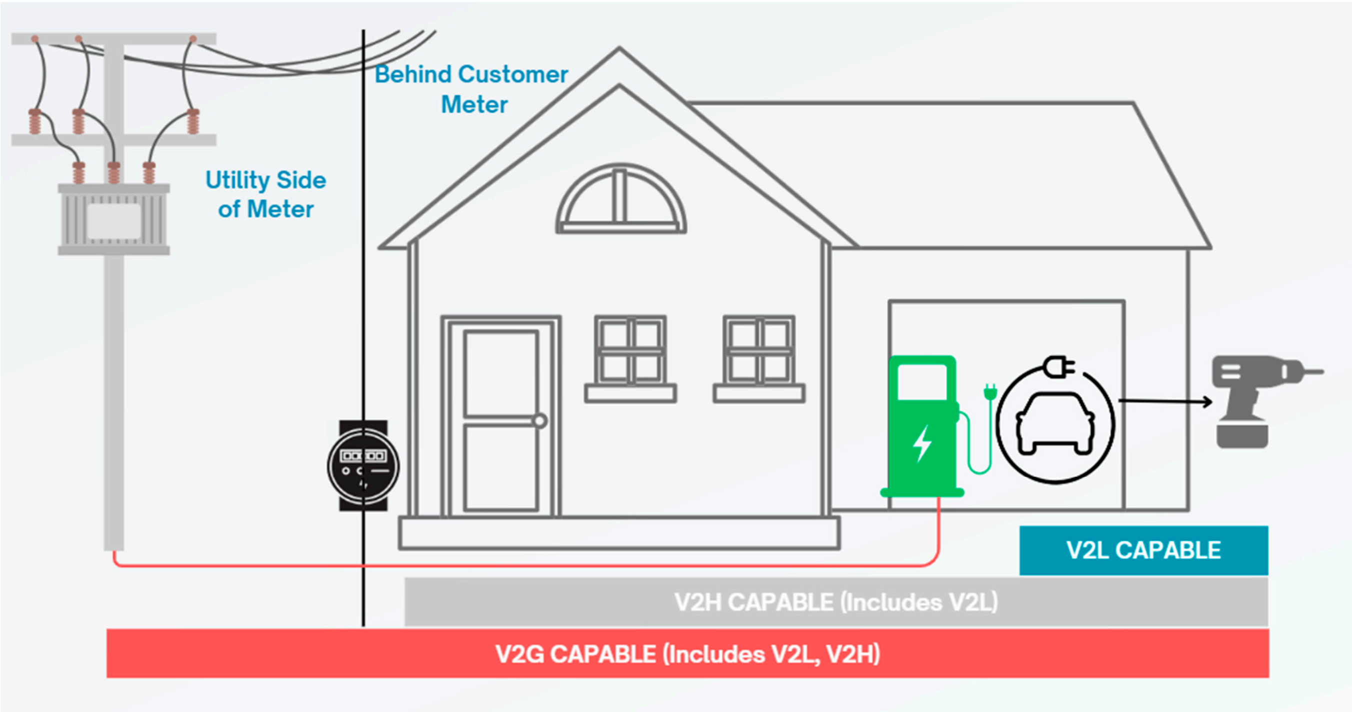

Figure 4. Overlay of V2X configurations, adapted from [32].

3.4. Summary of V2G Adoption Challenges

The previous section outlines various advantages of V2G technology across different applications. These benefits include grid support and stabilization, where EVs contribute to essential grid services like frequency regulation, thereby enhancing the grid's reliability and resilience. Additionally, V2G and V2M applications aid in the integration of renewable energy sources by storing surplus renewable energy, promoting a more sustainable energy mix. For EV owners and operators, participating in grid services and utilizing time-of-use tariffs can result in cost savings and revenue opportunities. In emergency situations, EVs can also provide critical power supply to homes and buildings (V2H/V2B), serving as backup power sources. Moreover, their ability to offer power in remote areas or during emergencies as V2L and V2V applications demonstrates the mobility and flexibility of EVs as dynamic energy sources.

Key disadvantages of bidirectional charging include however the accelerated wear and tear on EV batteries due to frequent charging and discharging, which can diminish their lifespan and efficiency [41]. The implementation of bidirectional charging on a broader scale poses significant infrastructure challenges, necessitating major upgrades to existing electrical systems and charging station equipment to mitigate the adverse effects that bidirectional charging could pose to the grid [42]. Additionally, the absence of universal standards and clear regulatory frameworks presents a notable obstacle to the widespread adoption of this technology [43].

Barriers in market participation for EV owners, such as access to energy markets, pricing mechanisms, and fair compensation models, also pose significant hurdles to bidirectional charging [7]. Lastly, the increased connectivity required for smart grid integration brings about cybersecurity concerns, highlighting the need to safeguard sensitive user and grid data [44]. Overall, while bidirectional charging offers numerous benefits, these challenges are broad and complex in nature. This paper delves into the disadvantages and challenges associated with bidirectional charging applications, with a particular focus on addressing the issue of battery degradation through data-driven mitigation strategies.

4. V2X Case Studies Survey

In a case study survey conducted by the Smart Electric Power Alliance (SEPA), Brittany et al. present six case studies showcasing real-world bidirectional charging projects and programs [32]. Three case studies feature customer projects and three highlight utility programs. The customer projects demonstrate V2B applications using light-duty EVs to reduce building peak demand (North Boulder Recreation Center) and participate in a transactive energy rate (Plymouth State University). The third customer project from Revel Rideshare features a small commercial EV fleet conducting V2G discharges to generate revenue through demand response programs. The utility programs include Dominion Energy's V2G electric school bus program, National Grid's V1G and V2G demand response offerings (Note V1G in this context refers to managed controls of charging while V2G refers to grid tied bidirectional charging), and Pacific Gas & Electric's (PG&E) variety of V2X pilots exploring different applications of bidirectional charging. Common goals across the projects and programs are understanding the technology capabilities, economics, and grid value of bidirectional charging, which will help inform future scaled programs. Key partnerships with charging and software providers like Fermata Energy are also critical for enabling and optimizing these applications [45].

While still in early stage, these initiatives demonstrate bidirectional charging delivers economic value to customers and grid services that benefit utilities, laying the foundation for broader adoption. Table 1 is a summary of the Bidirectional charging real world applications included in the survey presented. The SEPA report on the state of bidirectional charging in 2023 [32] presents a vendor landscape of vehicle manufacturers, models and their supported V2X applications. The report also presents a list of bidirectional-capable electric vehicle service equipment (EVSE) and charger vendors in the North American market.

Table 1. Bidirectional charging real-world case study summary.

Project/Program	Type	Application	Goal	Key Partners	Value Preposition
North Boulder Recreation Center [46]	Customer	V2B	Peak demand reduction	Fermata Energy	Lower demand charges
Plymouth State University [47,48]	Customer	V2B & transactive energy	Electricity arbitrage & peak reduction	Fermata Energy, Bellawatt, NHEC	Additional revenue
Revel Rideshare [45,49]	Customer	Fleet V2G	Understand V2G value proposition	Fermata Energy, NineDot Energy	Demand response revenue
Dominion Energy [50–53]	Utility	School bus V2G	Understand V2G capabilities	Proterra, EPRI	Grid services TBD
National Grid	Utility	V1G/V2G demand response	Test new demand response resource	ev.energy	Peak demand reduction
PG&E [54–56]	Utility	Residential & commercial V2X pilots	Explore different V2X applications	California Public Utility Company (CPUC)	Backup power, optimize charging, distribution deferral

5. Impact of Bi-Directional Charging Patterns on Battery Aging

5.1. Battery Aging Mechanisms

Battery cell aging implies irreversible changes that occur in a battery over time and have adverse effects on battery performance and dependability [57]. These phenomena continue to be a topic of research, and the variability with which it impacts battery performance makes it difficult to model. However, it is critical to qualitatively and, as much as possible, to quantitively understand the aging phenomena from a practical standpoint, both for safe EVs operation in V2G modes, as well as to help consumers understand the costs of participating in V2G programs.

Cell aging can be quantified by two simple concepts: capacity fade and power fade. Capacity fade occurs when the total capacity of a battery (the total amount of energy that can be retrieved from the battery, and the round-trip efficiency of the charge/discharge cycle) also decreases over time. Capacity fade is typically the metric used in determining the end-of-life (EOL) of a battery pack or cell by original equipment manufacturers (OEMs), which is typically between 70% and 80% of the original capacity for EV applications. This type of aging is correlated with loss of active lithium inventory (i.e., decrease in the active material capable of storing energy by lithiation/delithiation processes) [58].

Power fade, sometimes referred to as impedance increase, means the decrease of the power that a battery can deliver at the rated voltage, usually correlated with calendar time as well as with charge/discharge power levels used in the batteries' history. As the term impedance increase implies, it correlates to an increase in the equivalent series internal resistance of the cell or pack, which is a major factor in the power calculation or state of power (SOP) determination of an EV [59,60]. Power fade occurs primarily as a consequence of growth of the solid-electrolyte interphase, which causes mass transfer of the lithiation/delithiation to decrease, thereby resulting in the mentioned increase in battery internal impedance [58].

Both fade processes occur primarily due to side reactions within the battery and are exacerbated by more strenuous battery operating conditions.

The aging mechanisms of batteries can also be classified into two different types of aging: calendar aging and cycle aging. When a battery is in a no-load state (i.e., no discharging or charging is actively taking place), the capacity loss during this time is known as calendar aging and the dependency of the fade is attributed to the storing conditions of the battery, such as its state of charge (SOC) and storage temperature. Conversely, when the battery is loaded (i.e., the battery is charging/discharging), the capacity fade in this scenario is considered to be cycling aging. The cycling aging is characterized by the different operating conditions of the battery such as the charging rates (C-rates), charge throughput, depth-of-discharge (DoD), and the temperature of the battery. The convoluted nature of the factors that play a part in cycle aging makes the degradation mechanisms in this state difficult to predict [61].

The common degradation mechanisms of Li-ion batteries are summarized below:

SEI Growth: The solid electrolyte interphase (SEI) layer forms on the electrode surfaces during initial charging cycles. This layer is crucial for stable battery operation as it prevents continuous electrolyte decomposition [61]. However, continuous SEI growth consumes lithium ions and electrolyte, leading to increased resistance and decreased capacity. The extent of degradation depends on factors like temperature and state of charge.

SEI Cracking: With repeated charging and discharging, the SEI layer can become stressed and crack due to volume changes in the electrode materials. This exposes fresh electrode material to the electrolyte, causing further SEI growth and accelerated capacity loss. The impact of SEI cracking is typically seen as a gradual increase in resistance and a drop in capacity [62].

Particle Cracking: Active material particles in the electrodes can crack due to repeated lithium ion insertion and extraction, leading to loss of electrical contact within the particle [63]. This results in a decrease in the active material available for reaction and a gradual capacity fade.

Particle Isolation: Linked to particle cracking, this occurs when cracked particles lose electronic contact with the rest of the electrode, rendering them electrochemically inactive. This leads to a reduction in the effective capacity of the electrode and overall battery [63].

Electrode Delamination: Mechanical stresses can cause the active material to delaminate or peel away from the current collector. This results in a loss of active material and a significant drop in capacity [64].

Lithium Plating: This occurs when lithium ions are deposited on the anode surface as metallic lithium during charging, especially under conditions of low temperature or high charging rates. Lithium plating reduces the number of lithium ions participating in the charge-discharge process, leading to capacity loss and potential safety risks [61].

Current Collector (Copper) Dissolution: In some cases, especially under high voltage or acidic conditions, the copper from the anode current collector can dissolve into the electrolyte. This can lead to the loss of electrical connectivity and structural integrity within the anode, further degrading battery performance [65].

Each of these mechanisms contributes to the complex process of battery degradation in different ways. Quantifying their impact can be challenging due to the interplay of these processes and the variety of factors that influence them, such as temperature, state of charge, charging rates, and cycling depth. Advanced diagnostic techniques and detailed analysis are often required to isolate and quantify the specific contributions of each degradation mechanism in a given battery system. Table 2 is a summary of degradation mechanisms, operating conditions that exacerbate them, and the mitigation methods for avoiding such aging.

Table 2. Aging mechanisms summary.

Degradation Mechanism	Operating Conditions	Mitigation Methods	Research References
Solid electrolyte interphase (SEI) growth	High temperature, depth of discharge (DoD), high C-rate, State of Charge (SoC)	Maintaining lower temperatures, reducing DoD, managing charge/discharge rates	[61]
SEI cracking	Fluctuating temperature and SoC, irregular charge/discharge cycles	Temperature control, consistent cycling, avoiding deep discharges	[62]
Particle cracking	High C-rates, extreme temperatures, deep discharge cycles	Gentle cycling, temperature management, limiting depth of discharge	[63]
Particle isolation	Repeated deep discharge, high C-rate cycling	Limiting depth of discharge, moderating charge/discharge rates	[63]
Electrode delamination	Mechanical stress due to temperature fluctuations, uneven charge/discharge	Stable operating temperature, uniform charge/discharge practices	[64]
Lithium plating	Low temperatures, high charging rates	Charging at moderate rates, avoiding charging at low temperatures	[61]
Copper dissolution	Acidic conditions, high voltage operations	Avoiding operation at extreme voltages, ensuring stable electrolyte pH	[65]

5.2. Aging-Aware Optimization of Bidirectional EV Charging

Given the complexity and convoluted nature of Battery degradation mechanisms, advanced methods of modeling and detection of aging have been proposed in the literature. Guo et al. introduce a transfer learning method based on a back propagation neural network for the parameter identification of aging lithium-ion batteries, effectively reducing the complexity of the identification process [65]. Ngo et al. present a classical–quantum hybrid machine learning approach to model the nonlinear degradation process of lithium-ion batteries, showcasing the potential of quantum neural networks in battery modeling [66]. Unagar et al. presented a reinforcement learning-based framework for inferring calibration parameters of battery models in real-time, significantly enhancing accuracy compared to conventional methods. The framework does not require labeled data samples of observations and ground truth parameters [67].

Additionally, these methods must incorporate these aging models into the controls and optimizations of the battery management system for the efficient operation of the battery. Yang et al. propose a reinforcement-learning-based, health-aware, fast-charging control scheme for lithium-ion batteries, addressing the compromise between charging time and battery degradation [68]. Cao et al. address the optimization of battery energy arbitrage considering battery degradation, using a model-free deep reinforcement learning approach [69].

For EV bidirectional charging specifically, it is important to understand the use case and the duty cycles that the batteries will operate in to assess the degradation likelihood of the battery and thereby mitigate the effects of degradation by aging-aware optimization of the battery controls. Schwenk et al. integrated an aging-aware model into a smart charging use case and compared it with measurements of real EV charging. The results show that disregarding battery aging underestimates EV operating cost by approximately 30% and that the profitability of V2G applications is highly dependent on battery aging [70].

The impact of battery operational parameters, such as state of charge (SOC), depth of discharge (DOD), operating temperature and charge throughput (C-rate) cannot be overstated. Wikner et al. [71] perform an extensive series of tests on graphite and NMC/LMO-based Li-ion batteries, over a period of 3 years in various 10% SOC intervals. The degradation of the cells as a function of the cycles is established during these experiments and the findings indicated that limiting the Depth of Discharges to small ranges and maintaining the battery at a 50% State of Charge can enhance the vehicle battery's lifespan by 44–130%, focusing solely on aging caused by various driving patterns. Additionally, when considering the impact of calendar aging, it was evident that this factor constitutes a significant portion of the overall battery aging. By keeping the battery at 15% SOC during periods of inactivity and minimizing the duration at high SOC levels, the effects of calendar aging on the battery could be significantly diminished.

The specific chemistry of a cell will also impact its Bidirectional charging application and subsequent aging mechanisms. Geisbauer et al. [63] analyzed the capacity loss and impedance increase due to calendar aging across six cell chemistries. They found that capacity loss was most significant at 60 °C and higher storage voltages. This was notably evident in $LiNi_xMn_yCo_{1-x-y}O_2$ (NMC), $LiNi_xCo_yAl_{1-x-y}O_2$ (NCA), and $Li_4Ti_5O_{12}$ (LTO) cells at this temperature. NMC and NCA cells at 60 °C and high storage voltage experienced complete breakdowns due to their current interrupt mechanism being triggered. The study focused on calendar aging of cells and not cycles, however different states of charge and temperature conditions were examined. The tests were performed at different voltage levels for the cells, low, medium and high voltage. Their findings concluded that different cell types exhibited varying responses to calendar aging. For example, LMO cells at 50 °C showed minimal degradation, while LTO cells had the highest capacity decrease at high storage voltages but the least increase in internal resistance [72]. This could for instance indicate that LTO batteries may not be great for backup power applications where a high SOC/high storage voltage is needed over long durations of time (120 days), because of the infrequency of backup events, and the desire to retain high capacity in the batteries.

A study by Dubarry et al. [73] investigating the effects of V2G on the aging of battery cells—particularly focusing on capacity loss, resistance increase, and rate capability under calendar aging—found that implementing V2G twice a day led to a 75% increase in capacity loss and a 10% increase in resistance. Even reducing the V2G to once a day resulted in a 33% acceleration in capacity loss and a 5% increase in resistance. These results indicate a significant negative impact of V2G on cell health under mild conditions, potentially reducing the battery pack's lifetime to under 5 years. Interestingly the study also found that delaying charging using grid-to-vehicle (G2V) compared to immediate charging had minimal impact on capacity retention (<1%) and a limited effect on resistance (<5%) at room temperature. However, the study suggests that in warmer climates, delayed G2V might induce less degradation and thus be more beneficial. On the contrary, Troung et al. [61] argued that charging strategies like time-shifting charging combined with smart charging schemes with V2G, discharging some of the battery capacity to the grid/load to precondition the battery to an optimal SOC, are capable of mitigating the total aging process from 7.3–26.7% for the first 100 days of operational life and gradually vary to 8.6–12.3% for one-year continual operation compared to the reference standard charging approach [61].

A major shortcoming observed in the current literature is the absence of experimental studies to reach a consensus on the degradation effect of smart charging concepts. However, the experimental studies are not so simple to accomplish as they could take years to complete and might be obsolete by the time the tests are completed due to the rapid evolution of battery technology, their applications and their controls [37].

The cost of energy delivered from the V2G process then must include the actual cost of the energy and the cost to battery degradation (i.e., $\$/kWh_{V2G} = \$/kWh_{charge} + \$/kW_{discharge} \times t_{discharge}$). As mentioned, EV battery degradation depends on multiple factors, such as temperature and operating conditions. To minimize degradation, it is common to limit the state of charge of a battery to the 80% range between 90% SOC and 10% SOC. The literature indicates that, in this case, the battery lifetime is dependent on calendar time and the used capacity in a quasi-linear manner. Therefore, a good estimate for the costs of this capacity fade may be:

$$Battery\ Degradation\ Cost = \sum_{t=1}^{End\ of\ Life} \left(C_{battery} \times \frac{Deg_{cycle}}{Cap_{useful}} + Deg_{calendar} \right)$$

where $C_{battery}$ represents the original costs of the battery, $Deg_{calendar}$ represents the degradation per unit of calendar time, and Deg_{cycle} represents the degradation per cycle of charge-discharge cycle. Cap_{useful} represents the useful capacity of the battery, again assuming that the capacity used is the central 80% of the total nameplate capacity of the battery, and t represents a number of time slices from a new battery to the end-of-life state [74,75]. Naturally, further modifying other parameters, like further reducing the level of charge, will further reduce the damage to the battery, thus decreasing the battery degradation costs, as summarized in [76].

Modelling of lithium ion batteries indicates that keeping batteries at a high state of charge without discharging (i.e., a parked vehicle at a high SOC that does not participate substantially in a V2X process) or a vehicle that is repeatedly cycles (whether by driving or participation in a V2X process) both lead to lifetimes on the order of 10 years for the batteries [75].

This suggests that other estimates of a daily battery degradation cost of ~0.025%/day ~ 0.05%/day reported elsewhere are reasonable, though heavily dependent on average battery temperature and rate of charge and discharge [77]. This indicates that costs of V2G integration will significantly vary by location, and that modelling of battery degradation rates for specific locations to inform participants in V2G portions of VPP schemes is needed.

6. Continuing and Future Research

As bidirectional charging continues to play a pivotal role in enhancing grid flexibility and stability through V2X applications, the field of battery life prediction is increasingly influenced by data-driven approaches and state-of-the-art AI and machine learning models. This includes the use of sophisticated self-attention mechanisms and ensemble models that integrate these mechanisms with long short-term memory (LSTM) networks to develop more precise aging models for batteries [78,79]. Such advancements underscore the need for extensive experimental testing of bidirectional charging impacts across various battery chemistries and under different duty cycles and use cases, such as V2G and V2B in addition to real-world telemetry of battery parameters undergoing use in such applications. These models aim to establish quantitative thresholds for battery aging acceleration, as these models become more effective and accurate when trained with a relatively large corpus of data. There is a growing emphasis on designing universally adaptive, model-based, or data-driven aging detection frameworks. These frameworks are essential for improved battery diagnostics and lifetime estimations, key factors in boosting the widespread adoption of bidirectional charging in VPP applications.

Recent advancements in reinforcement learning and aging-aware controls specifically tailored for bidirectional charging are proving vital in enhancing the cycle life of Li-ion batteries, particularly in V2G contexts. These AI-driven approaches are not only augmenting current understanding and methodologies but are also paving the way for more resilient and efficient battery usage in the evolving landscape of renewable energy and smart grid technologies.

7. Conclusions

Considering the increasing renewable generation and electrification, bidirectional charging and V2X configurations enable electric vehicles to become dynamic, value-adding participants in grid operations. This research review offers key insights into existing capabilities, applications, and real-world projects at the customer and utility levels exploiting vehicle batteries for additional grid flexibility. However, aging mechanisms induced by repeated charging-discharging must be addressed through ongoing fundamental studies, advanced battery management algorithms, improved component designs, and demonstration at scale to cement bidirectional charging's future. Significant progress on understanding aging-reliability trade-offs will be integral for EVs and charging infrastructure to unlock their full potential within an increasingly complex energy ecosystem.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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