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Review

A Systematic Review of Optimization Approaches for the Integration of Electric Vehicles in Public Buildings

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Abstract: Electric vehicles (EVs) can provide important flexibility to the integration of local energy generation in buildings. Although most studies considering the integration of EVs and buildings are focused on residential buildings, the number of publications regarding large buildings, in particular, public buildings (PBs), has increased. However, the quantity of studies regarding the integration of EVs and PBs is still limited. Additionally, there are no review studies approaching the integration of EVs and buildings in one single framework. In this sense, this review aims to address the challenges and trends associated with optimizing the charging of EVs in PBs by conducting a systematic review of the existing literature. As contributions, this work develops a review that approaches the integration of EVs and PBs using multiple strategies and structures, presents an integrated picture of the technical and economic constraints, and addresses the future trends and research perspectives related to the subject. Through the use of an open-access search engine (LENS), a cluster of 743 publications was analyzed using two strings and a timeframe restriction. The most important contributions regarding optimization strategies and their evolution are presented, followed by a comparison of the findings with other review papers. As key findings, technical and economic constraints are identified (uncertainties of driving behavior and local generation, battery degradation, "injection tariffs", etc.), as are future trends and perspectives (local generation legislation, incentives for purchasing EVs, energy communities, etc.).

Keywords: electric vehicles; public buildings; charging; optimization; building microgrids

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1. Introduction

In the race against the clock to minimize the effects of climate change caused by greenhouse gas (GHG) emissions, the decarbonization of all areas is needed, with great attention being paid to the transportation and energy sectors. In 2020, the energy sector was responsible for 73.2% of global GHG emissions, while transportation and buildings (residential and commercial combined) emitted 16.2 and 17.5% of global emissions, respectively [1]. Additionally, the number of electric vehicles (EVs) increased significantly in the last years, as reported in [2], where a global panorama is presented in Figure 1.

Figure 1 presents the latest global sales of EVs from 2016 to 2022, and the individual numbers of EV sales for each year in each country are presented in the lower part of the table, expressed in millions of registrations. Additionally, an expected scenario for the whole year of 2023 is projected. Referred to as "2023E", the numbers are estimated based on the market trends from the first quarter of 2023. Moreover, the global market share of EVs grew from 4% in 2020 to 14% in 2022, and it is estimated that in 2030, 5 million oil barrels will be avoided. Additionally, the report provided by [2] also shows that recent policies regarding EVs in the USA (e.g., California's Advanced Clean Cars II rule) could increase the market share of these vehicles to 50% in 2030. Furthermore, there was a 65%

global increase in demand for electric passenger car batteries, representing 550 GWh of production capacity in 2022 against 330 GWh in 2021. The tendency is for these numbers to keep growing in the next decades. However, the biggest challenge in promoting the dissemination of EVs and simultaneously decreasing GHG emissions is to ensure that the electricity used to charge the EVs comes from renewable energy sources (RES), such as solar, wind, and hydroelectric generation, which have the greatest capacity today. In this sense, Section 1.1 presents the importance of integrating RES with EVs and discusses some studies that approach the topic.

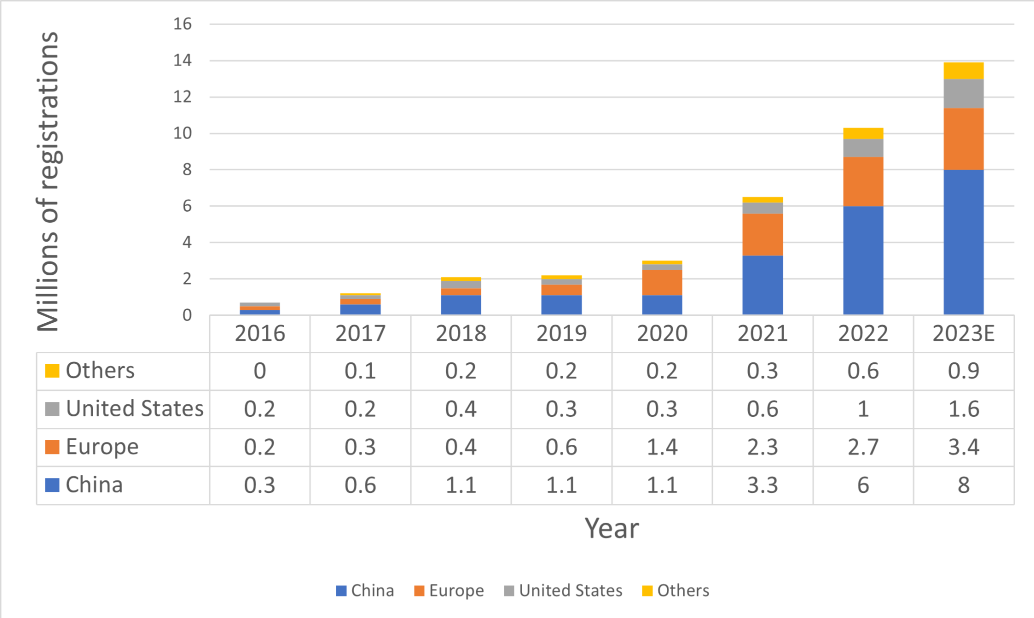

Figure 1. Global sales of electric cars from 2016 to 2023E. Data from [2].

1.1. Integration of RES and EVs in Buildings

Concerning the complete transition to clean energies, considerable progress has been achieved by increasing the share of RES in the global electricity matrix, highlighting wind and solar power [3,4] due to their cleanness and, in the case of solar power, easy integration into buildings through building-integrated photovoltaic (BIPV) technology [5,6]. Among the multiple challenges regarding this topic, two of them present a higher difficulty level, namely, the uncertainty of local energy generation and EV charging demand and the development of an optimal energy management system (EMS) that can simultaneously consider multiple components. As examples of advancements developed to address these challenges, Ref. [7] proposed an EV-based decentralized charging (EBDC) algorithm based on model predictive control (MPC) to optimally coordinate the charging of EVs in buildings integrating wind turbines dealing with the uncertainty of local generation and charging demand. The balance of the system was improved, and the combination of this method with event-based optimization was suggested as future work.

Ref. [8] used BIPV technology to assess the economic potential of charging an e-car-sharing fleet of a residential building considering multiple agents in Austria with mixed integer linear programming (MILP) as the chosen optimization strategy. Through the analysis of various scenarios, the results showed that the proposed model reduces energy costs by up to 29% depending on the scenario. Furthermore, Ref. [9] also applied BIPV to address both challenges simultaneously at an office building through the development of two new algorithms, namely, stochastic programming and load forecasting, for energy management with two stages (SPLET) and sample average approximation-based SPLET (SAA-SPLET) with the participation of both day-ahead planning and real-time operation. The combined use of these algorithms generated an average reduction in costs of 7.2% for SPELT and 6.9% for SAA-SPET. In the following section, Section 1.2, we discus disruptive vehicle-to-grid technology and consider its advantages and practical cases as they align to this work.

1.2. Vehicle-to-Grid Technology

Decarbonizing the transportation sector plays a vital role in mitigating the effects of climate change [10], and internal combustion engine vehicles (ICEV) are being gradually replaced by technologies with lower emissions, such as natural gas, liquefied petroleum gas (LPG) [11], and even biofuels, as is the case of ethanol and biodiesel [12,13]. However, the contribution of these technologies to reducing GHG emissions is small, and only electrification, taking advantage of the increasing share of RES in the electrical grid, can have a major impact. The powertrain options that comprise this shift are PHEV (plug-in hybrid electric vehicles) and BEV (battery electric vehicles) [14], since HEV (hybrid electric vehicles) and FCV (fuel cell vehicles) are not charged using the electrical grid.

Beyond contributing to lower emissions and a better quality of life in urban environments, EVs can be used as a flexible resource regarding (dis)charging management or even as a storage system [15,16] when integrated with the electrical grid, ensuring better resilience and safety for the entire system or at a microgrid (MG) level [17]. This technology is referred to as vehicle-to-grid (V2G) technology, and it will play a vital role in the context of smart cities. The main differential of V2G technology is the capacity of the EV to reinject electricity into the grid, which can greatly contribute to improving the match between local renewable generation and energy demand, and, consequently, can reduce energy costs. As disadvantages, V2G leads to additional cycles that will accelerate the degradation of the battery and requires the use of bi-directional chargers to allow the vehicle to trade energy with the grid, which is still too expensive to be implemented on a commercial scale, as well as the use of equipment capable of managing the energy flow between the entities. Ref. [18] compared the use of V2G and other charging strategies for an office building in Austria. Additionally, other benefits achieved when using V2G include grid load stabilization, improvements in renewable energy consumption, improvements in users' economic efficiency, and energy loss reduction [19]. Ref. [20] presented a review of V2G in terms of the advances already achieved and the challenges for the future. As an example of the previously mentioned capabilities, Ref. [21] discusses how EVs can be a flexible load resource for a car-sharing fleet. Additionally, the impacts at the economic and energy levels, as well as the challenges and prospects of the increased presence of EVs and their technological development, have been widely studied in recent years [22–27].

Ref. [28] studied the impact of the shift from ICEV to EVs on the electrical grid for a business campus in Portugal and discussed the current level of maturity and the future prospects of electric mobility at a national level. Another important level to consider is user behavior, where primary focus is given to the reasons that lead to EV adoption and how users typically use or want to use the EV and, consequently, the charging infrastructure. These factors together comprise the stochastic parameters of EV drivers and have an important role in the development of new methods for efficient energy management. In [29], a comparison between conventional vehicle users and BEV users was performed in Denmark and Sweden applying the "theory of planned behavior". The development of smart strategies such as one-slot look ahead (OSLA) [30] and the self-adaptive modified clonal selection algorithm (SAMCSA) [31,32] for the energy management and decentralization of energy generation through the interaction of EVs with parking lots and houses, and with increasing attention, public buildings (PBs) [33], will contribute to a stable, smart, and efficient electricity network and enhance the potential of vehicles as paramount tools of decarbonization.

The first interactions of EVs with the grid start in small environments such as charging stations (CSs), where PHEVs are connected to a charging station integrated with the main power grid and a local PV generation site [34]. The objective of the previously cited study was to charge the PHEVs with the maximum PV energy possible and alleviate the stress on the grid. The proposed control system was based on DC link voltage changes, which vary as a function of solar irradiation. With the proposed intelligent charging system, such operations did not impact the grid during peak hours. A different approach was proposed by [35] through the integration of 200 EVs with a smart parking lot and its EMS with the objective of reducing RES intermittence, improving the security of charging operations, and generating financial benefits for both the parking lot and the EV owners. In addition to successfully achieving the established goals, it was the first time that the energy reserve capability of these vehicles was demonstrated. On a larger scale, EMS was also applied by [36], where an integration system for PHEVs and a building was developed, focusing on maximum comfort for the users with minimal energy consumption. To address this challenge, particle swarm optimization (PSO) was used, and the comfort levels were maintained.

Ref. [37] developed the first CS with solar/wind generation integrated with the main power grid and V2G technology aiming to charge PHEVs and increase the matching between generation and demand. In [38], the CS system was further developed, with the inclusion of a fuel cell and electrolyzer system that generated electricity and hydrogen, respectively, to store the generation surplus using hydrogen. In addition, the system was a stand-alone system, meaning it was a completely independent operation from the main power grid. The interactions between EVs and buildings, with a focus on PBs, will be further detailed in Section 1.3.

1.3. Interactions between EVs and Buildings

The integration between EVs and buildings (residential and large PBs) occurs when the vehicle is connected to the building, regardless of the electricity generated in the building or provided by the grid. To increase the provided flexibility, a charger with bi-directional capabilities should be installed, meaning that the vehicles can be charged normally and can also work as a support system for local energy generation and decentralization of electricity generation. With this in mind, the need for smarter charging methods arises. Ref. [39] developed a smart method to charge EVs at home or in buildings using PV panels. Additionally, batteries can be integrated into the system, as seen in [40], where the authors integrated batteries with EVs in an MG using an artificial neural network (ANN) and a reverse Monte Carlo (RMC) method to optimally determine the most cost-effective configuration for PV–EV charging stations. The proposed framework had a 95% optimality rate, and the authors intended to consider EV bi-directional flow as their future work. The main advantage of such interactions can be an increased match between energy generation and demand using demand–response strategies [41,42], therefore minimizing the electricity imported from the grid. Additionally, a path to allow buildings to purchase energy from the EV owners and vice versa can be opened, enabling the creation of entire communities that generate and share their own electricity with each other, which are called energy communities.

In Figure 2, four different scenarios for a new building-to-vehicle-to-building ($V2B^2$) concept are presented. In this novel system developed by [43], houses and office buildings interact with each other and the grid at the MG level with the participation of PVs, EVs, and storage systems, evaluating the potential of the vehicles as energy vectors in the system. In all cases, the grid is always connected either to the house or the office building. For the first scenario, the conventional energy flow is represented, where both buildings receive energy from the grid in the traditional way, and the energy flow between the EV and the house is unidirectional, that is, it only flows to charge the vehicle. In Scenario 2, the house is equipped with PV panels and a battery (called a house stationary battery (HSB)), and the EV battery (EVB) can be charged either by the grid or by the HSB when a PV surplus is available. The novelty is that the EVB can transfer the potential electricity generated by the HSB to the office building, where the installed chargers can recharge the vehicle, if necessary. The operational logic of Scenario 3 is identical to Scenario 2, with the difference being that the house has a battery identical to the EVB. In this case, the batteries can be swapped, avoiding energy transfer from the HSB to the EVB (when recharging is demanded). Moreover, the EV can be recharged at the office (only for commuting purposes) and at home. Finally, in Scenario 4, the operational logic is identical to Scenario 3, but with the panels now installed at the building, and the house can be fed by the EVB (and also charge the vehicle for moving purposes, if necessary). Additionally, there are no stationary batteries at the office building, and the PV generation surplus is sold to the grid. Further, the authors used the computer simulation code DETECt 2.3 as the method to assess the energy demand of the building. The results show that financial savings were achieved (between 45% and 77% depending on the scenario), and the most important finding is that EVs are capable of working as an energy-transferring resource between houses and office buildings.

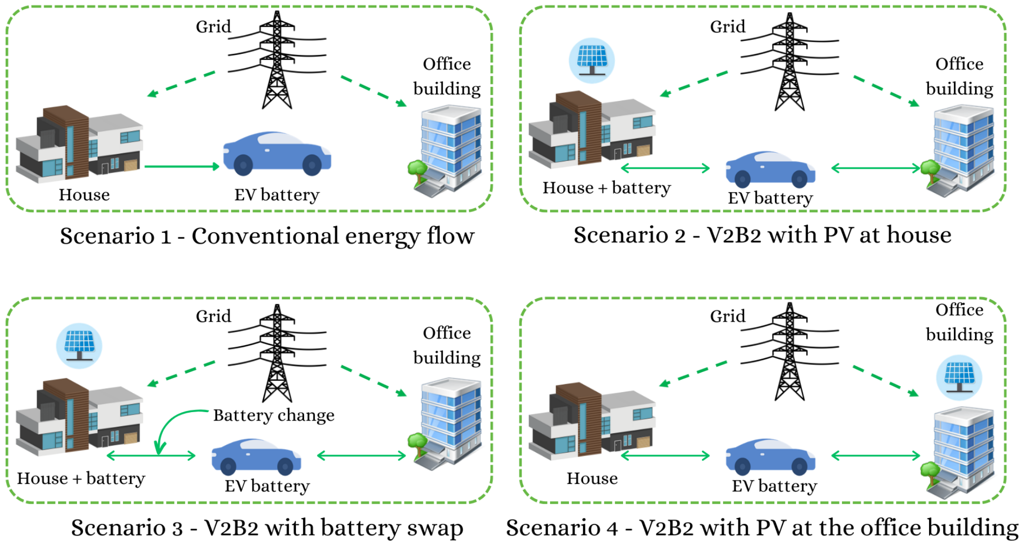

Figure 2. Different scenarios of the V2B2 concept.

Although important advances have already been achieved, there are still challenges that must be addressed, and together, optimization strategies must be found to increase the efficiency, reliability, and smartness of such novel systems. An MG management study involving EVs was performed by [44], where the authors developed a control strategy to reduce power factor issues caused by the inclusion of EVs and distributed generation (DG) resources for the referred MG. To achieve the objectives, dynamic programming was used. Through the results, it was noticed that the power factor remained above the reference value of 0.95 and that future work should consider voltage and frequency regulation. Some challenges to enhance the referred integration are pointed out by Refs. [45,46], such as incorporating the stochastic parameters of the vehicles and the occupants of the buildings, uncertainty in RES production, capacity expansion, etc.

1.4. Motivation and Contributions

This work intends to explore the missing gaps, constraints, and trends in integrating EVs and PBs, with a main focus on the optimization techniques applied to these cases. The main motivation for this study is that, until the present moment, there have been no studies that performed a review of the integration between EVs and buildings. Neither are there any studies if the focus is residential buildings or PBs. Additionally, some of the further-discussed multiple aspects involved in the optimization strategies (e.g., the use of V2G technology, battery degradation, policies oriented for RES and buildings, etc.) are presented from an individual point of view, exploiting the need to develop studies that comprise these characteristics in one single framework. In this sense, the contributions of the present research are denoted as follows:

- We provide a review and discussion of the integration of EVs and PBs using multiple strategies (e.g., V2G, V2B2, DG, etc.);

- We deliver an integrated presentation of the technical and economic constraints that influence the strategies applied to the main subject (e.g., time horizons, competitive tariff development, uncertainties related to local energy production and charging demand, etc.);
- We aid in the identification of trends and future perspectives of integrating EVs with PBs (e.g., energy communities, policies for new PBs, and policies for ICEV phase-outs), which can also be tools for creating new policies and regulations and future planning, aiming at the dissemination of sustainable buildings and EV adoption.

The remainder of this paper is structured as follows. Section 2 presents the strategy adopted for the literature review, while Section 3 presents the results of the literature review regarding the limitations of integrating EVs and PBs, as well as a collection of studies applying mathematical optimization (MO) and machine learning (ML) techniques. Section 4 discusses the contributions previously presented and identifies unsolved research questions. Finally, Section 5 presents the conclusions and next steps of the research.

2. Materials and Methods

The integration of EVs and buildings presented in the literature comprises mostly residential buildings, and when approaching the PB side, the number of references is still much smaller. However, an increase in awareness of integrating EVs and PBs was seen in the last few years, but with challenges to be addressed (which will be later discussed in Section 4). This work intends to present a systematic literature review of the above-mentioned subject and contribute to fulfilling the missing scientific gaps through presenting an integrated perspective of the constraints and trends related to the study. For a better understanding of the methodology, this section is divided into two parts. First, Section 2.1 presents the database and research software used for this review, as well as the strings/keywords and search stages. Second, Section 2.2 presents the results of the bibliometric analysis carried out.

2.1. Database and Research Software

In order to perform a systematic review of the integration between EVs and PBs, a database (which will also work as research software) is necessary to search the publications related to the subject. For this purpose, the Lens website search engine was used. Lens [47] is an open-access web platform that allows the user to search scientific publications on a specific topic and comprises all of the major scientific publishers known today (e.g., MDPI, Elsevier, IEEE, Springer, etc.). Moreover, beyond the normal features seen in other open-access search engines (such as Scopus, Web of Science, B-on, etc.), Lens presents statistics referring to the results, such as the number of publications for each year considered in the search, (which will be presented in the next subsection), the most cited works, and the universities with the most publications, the most active authors, and other parameters. The keywords used to perform the literature search and the document count are presented in Table 1 below.

Table 1. Query strings used in the LENS search.

Query	Document Count
(title: Electric AND Vehicles AND Public Buildings) OR (abstract: Electric AND Vehicles AND Public Buildings) OR (keyword: Electric AND Vehicles AND Public Buildings)	1418
(title: Electric AND Vehicles AND Public Buildings AND Review) OR (abstract: Electric AND Vehicles AND Public Buildings AND Review) OR (keywords: Electric AND Vehicles AND Public Buildings AND Review)	845

The selection of words was carried out in order to provide results aligned with the topic of this work and a good quality systematic review. The next subsection will present the steps taken with the applied methodology and the corresponding statistical results.

2.2. Systematic Review

This subsection presents in more detail the steps taken during the systematic review and the statistical results obtained. For both stages, only one filter was applied in order to provide a larger collection of contributions. More specifically, the results were restricted to the years 2012 to 2022 for a more recent perspective of the literature. The first research stage uses the string "Electric AND Vehicles AND Public Buildings" in the format presented in Table 1. As a result, a general perspective of the interactions between EVs and the grid is presented, where the scale of the environment evolves from small parking lots with solar panels to residential structures and buildings, and even some cases of larger buildings, with a focus on PBs. The initial obtained results on 10 May 2023 were a total of 1418 publications. After applying the timeline filter, the total of publications to be analyzed was 487, with its distribution over time being presented in Figure 3.

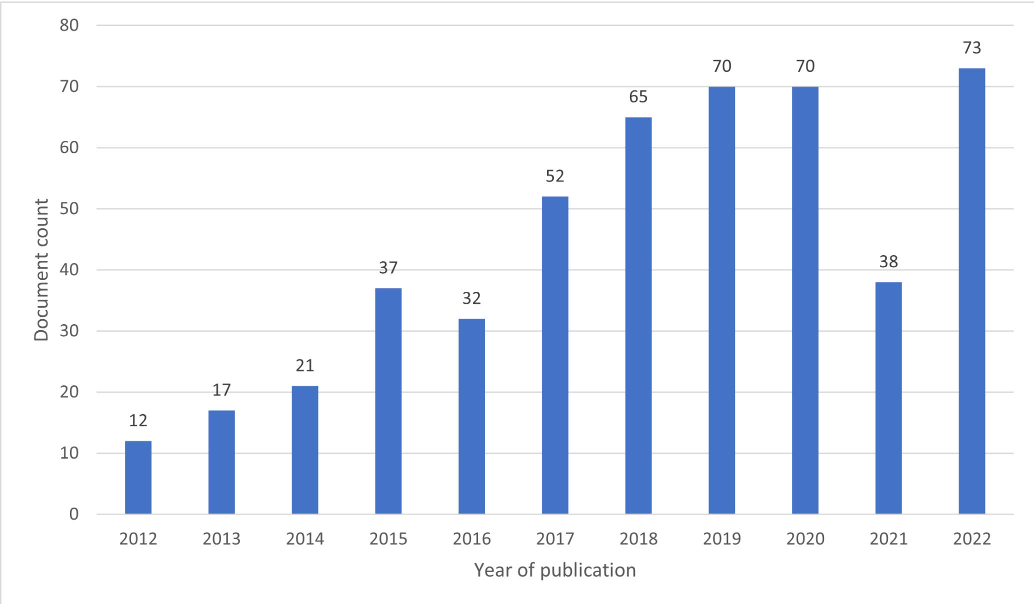

Figure 3. Number of publications over time for string "EVs" AND "Public Buildings". Data from: [47].

Figure 3 presents the evolution in the number of articles published from 2012 to 2022 for the string "Electric AND Vehicles AND Public Buildings". It can be noticed that there is a constant growing rhythm until the end of 2019 despite a small deceleration in 2016. However, between the years 2020 and 2021, there was a noticeable reduction in the number of publications. This was probably an impact of the pandemic outbreak with the lockdowns, since multiple field works were suspended, which reduced the number of published articles. In 2022, with the alleviation of measures and the re-initiation of scientific activities, the numbers returned to the same basis as before the outbreak. It is also possible to identify the top fields of study for the applied restrictions as they relate to the current literature search. This representation can be seen in Figure 4.

Beyond the presentation of the top fields of study related to the search, the number of publications for each field of study is also available in the figure, together with the corresponding bars. However, multiple scientific areas are shown in the Lens results, and most do not have a relationship with the subject hereby studied (e.g., biology, waste management, marketing, aerospace engineering, etc.). In this sense, a selection of the areas most aligned with this research was made, and the results are presented in Figure 4. For the second stage of the research, a comparison with other literature reviews regarding the integration of EVs and PBs was carried out, aiming to present their findings and identify where this work can contribute to the field. For this purpose, the "Electric Vehicles" AND "Public Buildings" AND "Review" strings were used to find articles focused on PBs. Accordingly, 845 items were identified, and after applying the same time period restriction

(2012 to 2022), the number decreased to 256. After the first classification of the findings using strings and filters, the contributions found were analyzed in such a way as to propose new questions and new strategies for integrating EVs and PBs. With the aim of better presenting the papers that were most aligned with the topic of this work, we classified them by their title, abstract, and relevance to this work. The final selection is presented in Section 3.

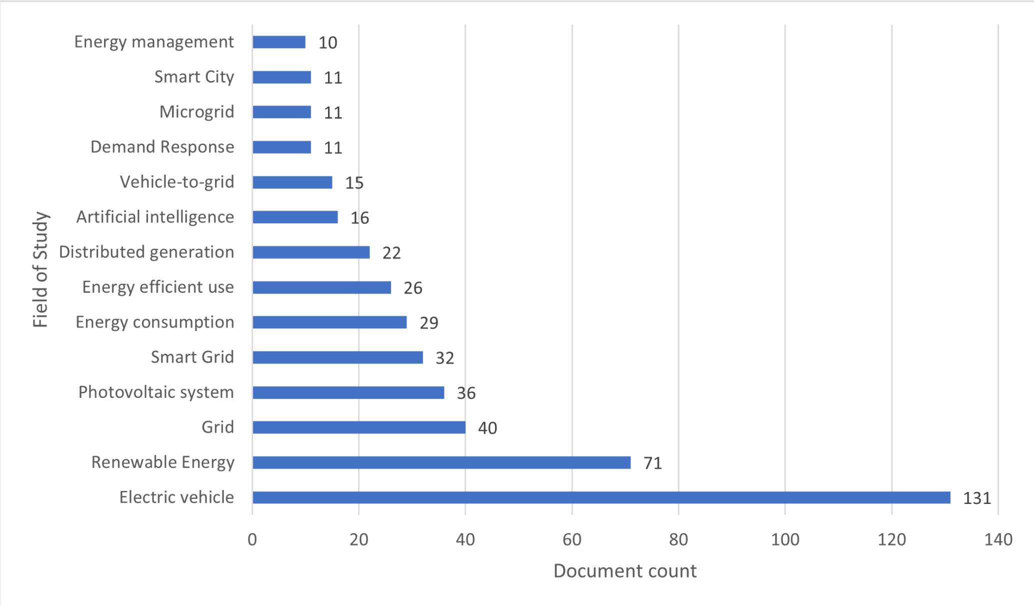

Figure 4. Scientific areas most aligned with the string "EVs" AND "Public Buildings". Data from: [47].

3. Results

The results of the literature review comprise a collection of contributions regarding the optimization challenges of integrating EVs and buildings, with a focus on PBs, the core of this work. Review articles about the topic are also presented to understand to which point this field of study has already evolved and what the challenges are that still need to be addressed. In this sense, this section is divided into two parts. Section 3.1 presents a collection of mathematical optimization (MO) contributions for the referred context, and Section 3.2 approaches the use of machine learning (ML) for the integration of EVs in PB.

3.1. Optimizing the Integration between EVs and PBs

Many techniques to integrate EVs and PBs can be utilized, from simple control systems to advanced approaches such as prediction using ML and MO [48–50]. Although this last technique has been increasingly chosen as the method for the aforementioned integration in recent years, there are still unfilled gaps in the literature regarding this. This section intends to present what is already known about this study's subject and identify the gaps that have not yet been addressed. A comprehensive review of different optimization strategies was presented by Refs. [51,52], where the creation of an EV fleet operator was proposed in order to reduce the adverse impacts of the larger number of EVs connected to the grid and the methods are classified by performance and applicability. For better organization, this subsection was divided into three subsubsections, according to the complexity of the environment. In this way, Section 3.1.1 presents simpler optimization cases, while Section 3.1.2 deals with MO techniques for buildings at an individual level. Finally, Section 3.1.3 brings to light the contributions of optimization in buildings at a community level.

3.1.1. Optimization with V2G in Charging Stations and Parking Lots

Ref. [17] developed a novel controlling system for a building-integrated MG (BIM) to maximize the use of local PV generation, minimize imported energy, and minimize the divergence of the desired departure SoC of the EVs. The authors used a finite horizon schedule scheme to develop the control algorithm. The model ensured that 85% of the energy needs were provided by PV generation. The forecasting accuracy will be improved in future investigations. Ref. [53] proposed an electric vehicle charging station (EVCS) using MPC and optimal control with minimum cost and maximum flexibility (OCCF) to maximize the flexibility capacity of the EVCS while minimizing operational costs through scheduled charging power. In addition, OCCF allows the EVCS to provide ancillary services to the grid. As limitations, power was not provided by the RES, and real EV usage data were not considered.

The authors of Ref. [54] aimed to minimize energy costs and the voltage deviation index (VDI) on a grid-connected unbalanced MG using an epsilon constraint and a fuzzy satisfying approach as methods to solve the multi-objective optimization problem. The results demonstrated that the model successfully achieved its objectives while handling stochastic uncertainties, and future work could include studying this method in an islanded mode. On a larger scale, the authors of [55] aimed to minimize the cost of a smart car park using V2G technology and a genetic algorithm (GA). These authors' results expressed the benefits of using V2G, and they concluded that such technology is influenced by factors such as battery degradation costs, feed-in tariffs (FIT), and the initial SoC. V2G technology was also studied by [56], where an optimization method to maximize self-sufficiency and charge EVs simultaneously using linear programming was developed, as well as [57], who presented a comprehensive review of V2G technology.

3.1.2. Optimization in Buildings at an Individual Level

The next contributions focus on vehicle-to-building (V2B) technology, where, as previously mentioned, the vehicles can act as energy storage systems for buildings and can also be aggregators of the MG. Ref. [58] proposed a single power contract for a smart residential building, aiming to determine the optimal contracted power value and the optimal schedule of charging/discharging the EV/battery storage. The model was formulated as a mixed binary linear problem (MBLP) and solved using GA. The proposed objectives were successfully achieved, and a 47% cost reduction was obtained compared to the absence of flexible contracted power and smart management systems. As limitations, the authors identified the need to incorporate demand response programs (DRPs) in further investigations.

V2B was also studied by [59], where a building-integrated photovoltaic (BIPV) system with bi-directional power flow between the grid and EVs was presented. Using multiple control methods (incremental resistance, INR; insulated gate bipolar transistor, IGBT; adaptive-filter-based control algorithm, and sinusoidal tracking algorithm), the authors managed to feed the building and the grid in both day and night periods while maintaining the load balance. Ref. [60] presented a novel system for energy management in buildings at an MG level called the optimal model for energy management strategy (OMEMS), involving PV, energy storage and EVs. Using MILP as the main method, the proposed model successfully maximized the use of RES and minimized the energy imported from the grid in a faster and simpler way compared with other methodologies. Ref. [61] used MILP to evaluate the cooperative capacity of an EMS that integrated RES, EVs, and ESSs in one single MG for an office building on a university campus. Six scenarios were analyzed with the objective of minimizing the total daily cost of electricity consumption, and the developed model was able to inject more power into the grid and allocate power to the components with greater flexibility in the scenario with the highest PV generation. Additionally, the model can be expanded and modified to add multiple building types and more loads, allowing it to be used at larger grid levels, such as for neighborhoods, for example.

A robust optimization model was presented by [19] to improve the security of an MG system composed of conventional generators, wind turbines, and EVs considering the uncertainty regarding the power provided by the EVs and wind turbines. The model accomplished its objectives and allowed the decisionmaker to adjust it for robustness or economy according to their needs. An optimization challenge on a larger scale was presented by [62], where the EV charging opportunities for private and public structures in Sacramento and San Diego (California, USA) were evaluated, considering infrastructure costs, dynamic electricity pricing, and the travel and dwelling behavior of BEV drivers. To address this case, the authors used MILP to determine the optimal location and the number of chargers with the lowest total system cost possible. The results showed that San Diego presents the lowest cost and the lowest emissions in comparison with Sacramento, even with a 48.9% higher number of drivers. However, factors that can affect the behavior of users, such as charging demand–price elasticity and price signals, were not considered. Additionally, the number of non-home chargers (30% of the required chargers for both regions in all scenarios) may have been underestimated, as the authors assumed that all drivers would be completely responsive to charging prices and that turnovers occur with perfect efficiency.

Ref. [63] addressed a larger challenge regarding demand side management (DSM) for a building integrating EVs, thermal energy, and storage units. With the objective of handling different pricing and solar availability, the authors developed a distributed approximate dynamic programming (D-ADP) algorithm that used feedback-based control. The model successfully achieved economic gains without affecting the comfort levels of the users. A similar work was developed by [64], where a discrete optimization strategy combined with DRP was proposed for the integration of residential EV customers in a distribution system through smart charging in a parking lot. The selected algorithm was MILP, and the desired SoC and next trips of the EV owners, obtained via an information sheet, were considered as well for four scenarios (normal or fast charging with and without the presence of DRP). The results showed that DRP effectively reduces battery charging costs and the peak load of the system without requiring any improvements be made on the existing electric grid system; additionally, it was found that normal charging presented better results than the faster mode.

3.1.3. Optimization in Buildings at a Community Level

A novel concept called a "boundary expansion scenario" (BES) was featured in [65]. The approach intended to expand the interactions of EVs with a solar-wind-powered office building from the parking lot to a remote parking space, allowing the vehicles to continue participating in the system regardless of their location. The green thinner arrows indicated the location of the EVs in relation to the office building, while the green thicker arrows referred to the energy flow between the EVs and the building. Regarding the black vertical lines, they represented the grid, and the horizontal black arrows indicated the electricity flow. Finally, the green thinner dots around the buildings and the vehicles encompassed the whole proposed system. The control strategy was based on the TRNSYS simulation software, which is used for evaluating building energy systems and services, on-site renewable energy and storage systems, and various control systems, as well. Two scenarios were assessed (non-activated BES and activated BES), with 10 and 20 EVs in use, respectively. It was concluded that, with the BES activation, the matching of generation and demand reached 62%, and the coverage rate of the EV storage was 96.9%. Figure 5 shows the potential interactions between EVs and office and residential buildings.

A community-level optimization novelty was investigated in [66], where EVs were considered as a "new-type" load in a distributed energy system (DES) combining solar power and hybrid energy storage systems (heat, batteries, etc.). The authors chose the non-dominated sorting genetic algorithm II (NSGA-II) to perform the optimization of the system due to its unique abilities in solving non-linear optimization problems, reducing computational complexity, improving calculation accuracy, and quickly sorting solutions.

The model was applied for 12 community scenarios with different levels, and the scenario with public buildings representing 50% of the community was found to have the best results, achieving 56.4% less GHG emissions and an energy saving rate of 53.1%. The authors of [67] modeled an energy sharing system called an electric vehicle–power grid–manufacturing facility (EPM) using mixed integer nonlinear programming (MINLP) as an optimization method to reduce energy costs and GHG emissions based on time-of-use (TOU) tariffs. This work is among the first to investigate the integration of EVs with manufacturing facilities. The model successfully proved its viability by reducing emissions and energy costs by 22% and 23% on average, respectively.

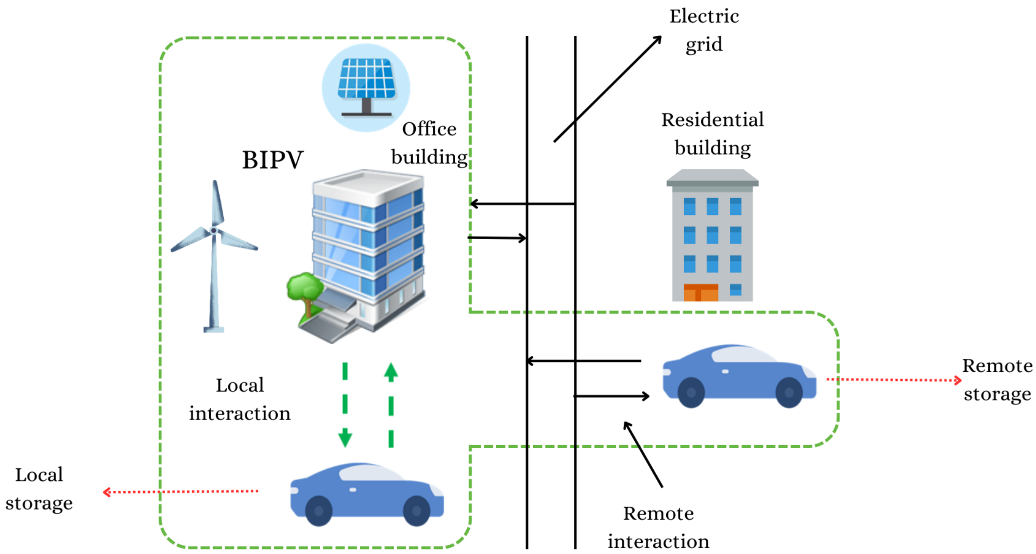

Figure 5. Interactions between EVs and office and residential buildings.

In Ref. [68], a day-ahead optimization model was developed for the Los Angeles Air Force Base Electric Vehicle Demonstration (LAAFB EVD) project, which incorporates 30 EVs and participates as a market resource in the wholesale frequency regulation market run by a California independent system operator (CAISO). The objective was to reduce the operation costs of the fleet while considering uncertainties such as the travel requirements of the EV owners, operational reserve capacity, building load, etc. The overall charging targets were met, and as future work, a stochastic optimization was suggested, as was considering battery degradation costs. In [69], optimization was applied to determine the number of allocated residential and PB parking lots for PHEVs in a distribution system (DS) that incorporated RES as distributed generation units and to minimize the overall energy cost of the system. For these purposes, the author chose the artificial bee colony (ABC) algorithm to assess the problem. Beyond reducing the overall expenses, the algorithm also improved the efficiency and security of the system. In [5], the authors proposed a strategy to maximize a green energy index (GEI) used for coordinating EV smart charging in a case study involving 510 EVs and 17 public BIPVs. The GEI allowed both EV owners and building users to be informed about the source that served their energy demand and the charging state of the vehicles, from time to time. To assess this challenge, the algebraic modeling language (AMPL) was used. The model successfully reduced the use of energy from the grid and simultaneously satisfied the requirements of the EV drivers, and future work will consider the stochastic behavior of the drivers, renewable energy, and building load.

3.2. Optimally Integrating EVs and PBs through Machine Learning Techniques

Although ML is mostly used for prediction purposes (e.g., [70–72]), this technique can also be used for optimization. Machine learning algorithms can be trained to predict the stochastic parameters (e.g., the desired SoC at the departure time, PV generation, the arrival time of the EV, etc.) related to EVs and PBs, and based on such results, the model can also optimize the problem such that one or more objectives can be simultaneously achieved (e.g., maximizing the use of local PV generation, minimizing the electricity bill, maximizing demand/generation matching, minimizing imported energy, etc.). Furthermore, in some cases, the model can be adjusted according to the user's preferences [19,56]. In this section, a set of contributions regarding the use of ML for optimization will be presented and analyzed.

The first example is Ref. [73], where a review was presented on the use of reinforcement learning (RL) in multiple applications with a focus on energy management, exploring the different RL algorithms and their performance when employed on EMSs. In [70], ML and MO were applied together to predict the availability of an EV to provide vehicle-to-home (V2H) services for a house. To predict the availability for five different vehicle usage levels, light gradient boosted machine (LightGBM) was chosen as the ML method. In the sequence, MO was employed using the Pyomo framework to minimize the electricity bill for each profile. The proposed model successfully reduced the household's electricity bills by 46% with a prediction accuracy of 85% and a coefficient of determination (referred to as R^2) of 0.78 for the journey length prediction.

Ref. [71] also used both ML and MO in one single framework, aiming to minimize the costs of purchasing electricity from the grid for a residential building in Belgium that comprised photovoltaic–thermal panels, batteries, and EVs. A supervised learning algorithm, gradient tree boosting ensemble (GTBE), was applied to predict the stochastic data (PV generation, load of the building and EVs, etc.), and in sequence, the obtained data were optimized through linear and mixed integer programming as a deterministic optimal control problem. Three scenarios were studied, and the results showed that a scenario with 20 kWp of panels combined with a 16.1 kWh battery capacity achieved the best performance (31% reduction in electricity costs, 68% of on-site energy fraction, and a 97% generation-to-demand ratio). A field test was implemented in [74] by deploying ML to maximize the self-consumption of multiple residential locations in The Netherlands including PV panels and buffered heat pump systems. In [72], the authors applied ML to predict the energy consumption of 2370 PBs in Chongqing (China) using six different regression algorithms (linear regression (LR), ridge regression, support-vector regression (SVR)—linear kernel, decision tree (DT), random forest (RF), and XBoost) together with a constant optimization process.

As already discussed, the charging demand is a vital parameter for the integration of EVs and PBs, and therefore, there is a need to predict such information. Ref. [75] applied ML to predict the EV charging demand of California for long-term planning based on real drivers' patterns. To identify such patterns, the authors used a hierarchical graphical-based approach in a probability tree format and a Gaussian mixture model as the chosen ML technique. The real data of drivers were also used by [76] to evaluate the energy consumption of EVs in China under uncertain and small data conditions. For this purpose, a machine learning control variable (MLCV) model was created with LightGBM as the base learner and later compared to other ML techniques (LR, DT, nearest neighbor Regression, SVR, and RF). The results showed that the MLCV model had a better accuracy of estimation than the other models, and the authors suggested the use of deep learning for future works in this area. The authors of [77] applied ML techniques to investigate energy consumption based on the occupancy of different spaces in the same institutional building. Aiming to model the interrelation between energy load and occupancy, a deep neural network (DNN) was applied and compared with five other ML methods (SVR, RF, gradient boosting (GB), artificial neural network feed-forward (ANN-FF), and a DNN-based artificial neural network (ANN-DN)). As a result, DNN and GB had the best prediction accuracy and comparison velocity, and they were integrated into one single model.

A different approach was presented in [78], where the authors evaluated how to combine big data and ML in an intelligent system for the energy management of public buildings in Croatia. Three ML methods were used (deep ANN, classification and regression tree (CART), and RF) for the prediction modeling, in which the RF had the best accuracy. The three models were integrated with big data in a system named MERIDA, which can improve the energy efficiency of the public sector and could become a powerful tool for decisionmakers to implement actions that will bring benefits both at the micro level (building) and the macro level (public sector).

The literature presented various contributions regarding the integration of EVs and buildings (integration of batteries in MGs comprising EVs and buildings [40], V2B technology [43], combined use of ML and MO techniques [70], etc.), as well as some limitations (absence of V2G, the need to consider stochastic parameters as future work, etc.). To better understand the pros and cons of the literature, a discussion will be promoted in Section 4.

4. Discussion

After gathering a collection of references related to the integration of EVs and PBs, this section intends to assess the progress already achieved by the previous research, identify the current limitations of optimization models, and assess which questions still need to be answered. In this sense, the findings are presented in the following format. Section 4.1 discusses the overall observations from the literature regarding MO, while Section 4.2 approaches the technical and economic constraints. Finally, Section 4.3 presents the policies and trends that will impact the integration of EVs and buildings.

4.1. General Observations of Mathematical Optimization

The first observation obtained from the literature is that there are no review papers focused on the integration of EVs and PBs in one single framework. However, multiple publications approach the aspects related to the subject from a more individual perspective (these aspects will be further described). In this sense, the need for a paper discussing the evolution of the integration between EVs and PBs in only one place reinforces the importance of this work as a novelty for the scientific community and allows to explore the referred subject in a deeper way.

Aiming to provide a larger panorama of the works previously mentioned, an overview is presented in Table 2. Focusing on MO, each of the 28 items shows the correspondent reference number, perspective, methodology, objectives, findings and constraints.

Observing Table 2, it can be noticed that most works focused on residential buildings, parking lots, and even power plants. Additionally, some papers studied EVs and PBs separately. This observation leads to the need to develop more research integrating PBs and to combine both the buildings and the vehicles in one single framework. Moreover, on the one hand, some contributions did not use a bi-directional power flow between the building or the grid and the EV (V2G and V2B), meaning that the vehicles were only charged, and the discharge of the vehicles to supply the building or the local grid was considered as future work. On the other hand, in the studies including V2G technology, the authors highlighted that the vehicles can successfully support local generation and work as mobile battery storage systems or provide ancillary services to the grid, which may have some limitations, such as variations in the range of SoC, battery degradation, FIT, and other aspects that will be further discussed.

Regarding the perspectives of the references hereby presented, it can be noticed that the most studied is the perspective of the grid, being present in almost all the articles, with the consumer and economic perspectives following right after. At first glance, this is a good impression, as half of the 28 works are oriented to deal with grid and consumer requirements, which is not the same when the optimization objectives are analyzed (which will be shortly discussed); most are oriented to minimize electricity bills or operational/overall costs (electricity, equipment acquisition and maintenance, degradation, etc.). In addition, almost half of the presented research handles two perspectives at the same time, and only one considers three simultaneously. In this sense, there is space in the literature to develop more works emphasizing the maximization of the generation/demand balance, as the integration of EVs and PBs will have a major impact on these stakeholders, as well as studies that comprise all the referred perspectives in one single framework.

Table 2. Overview of the references in the scope of MO.

Ref.	Perspective	Methodology	Objective (s)	Observations
[43]	Grid	DETECt 2.3	Max. generation/demand match	Energy savings between 45 and 77% More suitable energy policies are needed
[44]	Grid	Dynamic Programming	Max. PV generation usage Max. power factor	Power factor above the reference Addition of voltage and frequency regulation in future works
[53]	Grid	MPC OCCF	Max. EVCS flexibility capacity Min. EVCS operational costs	Cost reduction and ancillary services provision Absence of RES, real EV data, and battery degradation consideration
[54]	Grid	Epsilon constraint Fuzzy satisfying approach	Min. operational costs Min. VDI	Handling of uncertainties, islanded mode operation, and EV inclusion are suggested as future work
[55]	Grid	GA	Min. car park electricity cost	V2G benefits are seen but influenced by battery degradation cost, FIT, rebate, and SoC Absence of considering SoC requirements, driving patterns, V2G schemes, and RES
[67]	Grid	MINLP PSO	Min. total electricity costs	Electricity and emissions reductions are achieved Absence of EV driving and electricity price uncertainties Consideration of other RES as future work
[69]	Grid	ABC	Optimally determ. number and size of parking lots Min. total energy costs	Energy cost reductions were achieved Operational conditions were improved
[61]	Grid	MILP	Min. overall energy cost	Viability seen in scenario with most PV Possible expansion to neighborhood/district levels
[71]	Grid	GTBE MILP	Min. imported electricity cost	Best results with a 20 kWp PV and 16.1 kWh battery Applicability in other central European climatic areas

Table 2. *Cont.*

Ref.	Perspective	Methodology	Objective (s)	Observations
[40]	Grid	ANN RMC	Min. PV and battery configuration cost	95% optimality rate Consideration of bi-directional EV power flow is suggested as future work
[56]	Grid Consumer	Linear Programming	Max. local PV self-consumption Optimally charge EVs Min. grid energy import	The objectives were achieved User can set the desired parameters
[58]	Grid Consumer	MBLP GA	Max. demand fulfillment Min. electricity bill	47% electricity bill reduction Optimal contract power value determined DRP and economic viability as future work
[60]	Grid Consumer	MILP	Max. RES usage Min. imported energy	The objectives were achieved Better performance than other techniques
[5]	Consumer Grid	AMPL	Max. PV usage through GEI	PV energy satisfies EV and building needs Need to consider stochastic parameters of EV, building, and renewable generation No bi-directional flow between EVs and building
[32]	Consumer Grid	SAMCSA	Min. total operation cost	Cost reduction EVs enhanced to mobile storage systems Overall MG reliability improved
[33]	Consumer Grid	MILP	Max. consumer profits Min. electricity cost	15–20% electricity bill reduction Capacity to address overload situations
[17]	Consumer	Finite horizon Schedule	Max. local PV production Min. imported energy Min. departure SoC divergence	PV energy ensured 85% of loads Need to improve the forecasting accuracy No bi-directional flow between EVs and building
[30]	Consumer	OSLA	Min. operational costs Max. local generation usage	20.53% overall cost reduction 88.15% accuracy of customer load execution Include more buildings

Table 2. *Cont.*

Ref.	Perspective	Methodology	Objective (s)	Observations
[36]	Consumer	PSO	Max. customer comfort Min. energy consumption	Comfort levels maintained Use of market information and economic analysis for future work
[39]	Consumer	MILP	Min. electricity costs while satisfying SoC of EV users	Charging costs reduced Need to consider forecast errors and V2G in future work
[70]	Consumer	LightGBM Pyomo	Min. electricity bill Min. energy consumption	Electricity costs reduced by 46% House electricity demand, EVs' daily trip number, trip duration, and trip starting time were not considered
[74]	Consumer Economic	RL	Max. generation/demand match Min. electricity bill	50–75% increase in local PV coverage algorithm performance influenced by end-user behavior, PV forecast accuracy, and seasonality
[68]	Economic	MILP	Max. profits Min. operation costs	All SoC targets were met Absence of stochastic optimization and V2G costs (e.g., battery degradation)
[19]	Economic	SIP	Min. operation costs	Cost reduction and system improvement Adjustability to robustness or economy
[64]	Economic	MILP	Min. total energy costs	Charging costs minimized under technical and economic limitations Peak loads decreased without system upgrades
[66]	Economic	NSGA-II	Max. energy saving Min. GHG emissions Min. user annual cost	Objectives are accomplished Scenario of 50% of PBs with best results Building scenario design suggestions are provided
[62]	Economic Grid	MILP	Estimate EV charging infrastructure placement Min. operational costs	San Diego area presents the best results Introduction of factors such as price elasticity and price signals is suggested for future work
[63]	Economic Consumer	D-ADP	Min. operational costs maintaining comfort level	Energy and comfort cost benefits proved Absence of equipment degradation and maintenance costs (batteries, PVs, etc.)

Concerning the optimization techniques, it can be noticed that beyond the proper MO algorithms, ML techniques can also be employed for optimization, and there is an increasing variety of tools that can be used for integrating EVs and PBs, as some works even compare different algorithms to identify the best option(s) to achieve the proposed objectives. However, only a few contributions use both approaches at the same time, and the ones that do use only one technique of each type. In this sense, there is space to develop more works that employ both ML and MO together, as well as the possibility of adopting more than one option for MO and ML algorithms. Moreover, as previously mentioned, it is possible to notice that most of the optimization objectives are focused on the minimization of electricity bills or the overall/operational costs, and only a few of them aim to maximize the matching between local generation and demand. In some cases, the energy that feeds the system comes from the grid, and an absence of RES is noticed. In this sense, more future works should include RES with special attention to PV and the integration of EVs and PBs in the same framework.

4.2. Limitations and Constraints of Integrating EVs and PBs

This subsection describes the main constraints in the context of integrating EVs and buildings, which are generally classified as technical, economic, and political constraints. Moreover, for each perspective, they can be related to the EVs or the building, depending on the scenario.

4.2.1. Technical Limitations

Taking first a technical point of view, the constraints identified in Table 2 are related to the desired SoC at the departure of the vehicles, the usage of real EV data such as driving behaviors, duration of trips, charging/discharging power of the battery, and uncertainties related to these factors, and PV generation, which plays a vital role in the integration of EVs and PBs. Additionally, the load limit of the system is also an important constraint that restricts the amount of power provided by the grid and, in consequence, the number of loads connected to the grid, such as EV chargers. On the building side, energy consumption is also considered in many of the aforementioned studies, as it directly impacts the amount of energy that must be generated to meet the demand of the users (both the building and the vehicle) and the availability of stored energy or ancillary services. Another important aspect that was identified is battery degradation. This is one of the most important constraints as it can have an impact both on the technical and economic side of the integration. From the technical perspective, the battery degrades more quickly depending on the number of charging/discharging cycles and the depth of discharge, consequently decreasing its storage capacity over time. This is mainly critical when bi-directional charging is considered, since the number of cycles is increased. A review of different charging methodologies considering battery degradation is presented by [79].

An important figure that must be considered as a technical constraint is the time horizon chosen to be used in the optimization of the problem. The time horizon interval is key for the user to define the frequency and intensity of the actions taken by the optimization model in a certain interval ahead of the currently available information, meaning that the further ahead the model is calibrated to forecast, the more uncertainty will exist, as well as a smaller accuracy, resulting in different impacts depending on the selected time horizon. The time horizon can variate from a "rolling horizon" (based on real-time operations and data inputs) to day-ahead predictions and even horizons considering months or years of the foreseeable future, which are more suitable for medium- and long-term planning. In general, for optimization problems focused on operational and tactical solutions, the rolling horizon is more suitable [80].

As examples of optimization using different horizons, Ref. [81] developed an ordinal optimization (OO) model using real-time data and eight horizons of 15 min each to reduce the operational costs of a CS and deliver a probabilistic performance guarantee. In [82], a receding horizon approach was adopted to employ charging policies intending to minimize the daily peak power of a parking lot equipped with CSs while guaranteeing customer satisfaction considering arrival time, departure time, and demanded charging energy as uncertainties. For this model, the authors adopted a horizon of one day, and two algorithms were developed based on the above-mentioned approach, namely, the receding horizon policy (RHP) and receding horizon policy with prior information (RHPP). Additionally, only the CSs and plugged EVs relative to the current time step will be part of the RHP actions, as for this situation, the car park owner does not have any information on the uncertainties.

Finally, what is probably the most important constraint of all to be considered is the type of charger to be used. The chargers currently available in the market can charge electric vehicles either using an AC current at home or at standard public stations or using a DC current at fast charging stations. According to the EVEXPERT website [83], AC chargers have a power capacity of 11 kW or 22 kW (maximum), while DC chargers have a 50 kW standard output at fast charging points and, in some cases, can reach an impressive output power of 150 kW in ultra-fast charging stations, or even 250 kW, as is the case of Teslas's ultra-fast chargers. However, it is extremely important to understand the impacts that the different charger levels can have in the context of integrating EVs and PBs. In Europe, an AC charger level of 2 is standard for houses and slow public stations or workplaces [84]. DC fast charging is mostly available at motorway service stations and, with increasing presence, in PBs as well.

These charging levels will generate different impacts in terms of power delivery, infrastructure requirements, and charging time, especially if the chosen level is DC fast charging. Ref. [85] studied the impact of the peak demand of DC fast charging from plug-in electric vehicles in a PB in the USA and investigated the combined use of PV panels and demand management (DM) to mitigate the impacts caused by their penetration considering four different load scenarios (only the vehicles, vehicles and PV, vehicles and DM, and the three combined) and two charging profiles. The results showed that only the combination of PV and DM could keep the peak demand of the building with the vehicle's penetration lower than the original peak demand without any of these, and the consideration of stringent DM strategies as well as appropriately sized PV panels were stated as recommendations.

A different study was performed by [86], where the authors analyzed the feasibility of installing an EV charging station powered by PV panels in a university building in Poland considering the real driving conditions of an EV user (e.g., energy consumption and driving distance) using an 11 kW capacity charging station for the simulation, as well as testing driving conditions in summer and winter. The preliminary outcomes indicated that, with a 310 kWh daily PV surplus, the station could charge between 3 and 12 vehicles simultaneously, depending on their power, in an 8-hour working period. Moreover, at the current level of development, the participation of the power grid was still necessary, and consideration of varying daily sunlight conditions was pointed out for further investigation. In this sense, it was seen that different levels of charging have different impacts on the grid and users. Hence, it is extremely important to evaluate the local energy production capacity, building consumption, and infrastructure requirements to choose the right type of charger. Additionally, to achieve better generation–demand matching, it is recommended that research regarding the combination of PV and DM strategies should be carried out, seeking to avoid grid overloads in peak hours (end of the day) and a larger response capability to attend to the needs of both parties. Finally, it is also recommended that political and economic measures to disseminate EV public and fast charging should be carried out, such as the creation of incentives for EV charger acquisition, regulations to standardize charging levels, and even the development of new chargers that support both AC level 2 and DC fast charging in one single unit, allowing wider compatibility between the equipment and the vehicles, especially those with lower charging capacity limits.

4.2.2. Financial Limitations

The second constraint perspective is focused on the financial point of view of the subject, where there are costs associated to maintain the system operational (equipment acquisition, operations, maintenance, depreciation, etc.), and electricity tariffs between the building, grid and EVs. As previously mentioned, battery degradation can also play an economic role in the integration of EVs and PBs. In the case of battery discharge with the energy injected into the building or the grid, it is natural that the drivers receive financial compensation for having the flexibility provided by their batteries and the cost associated with the degradation must be compensated. Some of the previous constraints are identified by [87], where a combined assessment of technical and economic aspects is performed for a university campus using Battery Energy Storage Systems (BESSs) and V2G. The conclusions show that the main technical constraints are related to the efficiency of the charging and storage systems, and for the economic side, the availability of the EVs and the tariffs are the greatest challenges.

Highlighting the tariffs, the ones that can most limit the integration of EVs and PBs are the Dynamic tariffs and FIT. Dynamic tariffs, as the name indicates, are electricity prices that change according to the energy demand and availability at a given time. The more energy available and the smaller the demand, the lower the price will be. In the main context of this work, dynamic tariffs are probably the biggest challenge to address, as the predictability uncertainties turn harder for aggregators and energy operators to decide for which prices they will sell their energy, and influences the right time for buildings and EV users to decide when to buy energy.

With the decentralization and opening of the energy markets in many countries, there is a need to develop tariffs that allow the producers of renewable generation and EV owners to inject their energy into the grid for competitive prices in relation to the normal ones paid for electricity, known in general terms as "injection tariff". In the past, there was a type of tariff designed to increase RES electricity share through long-term power contracts called Feed-in Tariff (FIT) [88,89]. However, this tariff was much higher than the normal electricity price and was abandoned by most countries [90]. Nowadays, the most common tariff scheme for PV prosumers is net billing, where the injected surplus is rewarded with credits that are applied for offset consumption or a payment (generally lower than the normal electricity price) [91]. However, as the open energy market is still in the early stages of development, there is a need to develop policies that regulate the prices in a way to allow a fair and accessible market for everyone.

4.3. Future Policies and Trends

After an extensive analysis of the literature related to the integration of EVs and PBs, this subsection presents the future policies and trends associated with the literature and future perspectives for further development related to EVs and energy management in buildings. With the wider adoption of RES and EVs, and the increasing number of buildings with intelligent EMSs, new trends will rise and drive society towards a greener and smarter future. To turn these trends into reality, policies must be created for a faster shift toward sustainable energy generation and integration and allow fair access to these technologies for everyone.

4.3.1. Future Policies

The first political measure that will have a major impact on the integration of EVs and PBs is the regulation of PV panel installations in houses and buildings. Already being applied as law in some countries, this policy makes it mandatory for houses and buildings to have solar panels installed on their rooftops as a way to disseminate the use of renewable energies and to reduce GHG emissions. As an example, Ref. [92] recommends that PV panels must be installed in all new buildings and any buildings undergoing roof renovation inside the European Union (EU). In the USA, more specifically, in California, this policy already is law, obligating every new house or building to have PV panels installed.

Although this policy is still being studied and discussed in many places worldwide, it will be a standard in the future and will also be a great contributor to decarbonization. Moreover, there is also a need to develop policies that promote EV charging flexibility through tariffs and incentives (e.g., V2G-specific tariffs) [93].

At the end of 2020, according to the Energy Performance of Buildings Directive of the European Union (EU) Comission [94], EU countries needed to ensure that all new buildings were nearly-zero energy (NZE), and all new PBs were meant to be NZE after 31 December 2018. According to a proposed revision of the directive in December 2021, the document proposes that all new buildings must be zero-emission buildings (ZEB) beginning on 1 January 2030, while new PBs must meet this criterion beginning on 1 January 2027. As some studies have already shown, it is already possible to use PV generation to fulfill the energy needs of buildings and use the surplus to charge EVs, inject energy into the grid as an ancillary service, or even become self-sufficient in electricity generation. It is therefore essential to develop policies that allow the widespread adoption of such technology in a fair and accessible way for everyone. The great benefit will be the stability offered by the system, allowing it to generate local, clean, and accessible electricity, reducing dependence on the main power grid or even fully disconnecting from it. This possibility leads to an increasing trend already mentioned earlier, that of energy communities, which will be discussed shortly.

The last two political factors that will become great allies in the future are the incentives for purchasing EVs and the ICEV phase-out policies. The end of the production and commercialization of vehicles with combustion engines will be a reality over the next couple decades, and measures to accelerate the transition to a fully electric era are already being taken. It is already known that the EU will forbid the production and commercialization of new ICEVs beginning in 2035 [95], and many other countries will take the same path, although at different moments. Moreover, forbidding the production and sales of ICEVs alone will not be enough to accelerate the transition to electric mobility. It is extremely important to create financial conditions for society to have access to EVs and PHEVs (e.g., incentives to purchase EVs) and also create incentives for the installation of public chargers, with special attention for PBs. Additionally, financial support for the installation of bi-directional chargers must be developed, as this technology still has high costs. Hence, financial incentives must also be part of the policies for a greener future. Many countries already offer financial benefits and incentives for purchasing an EV or a PHEV, especially in the USA, Europe, and Asia, where the conditions for having these vehicles are more favorable, although not yet ideal.

4.3.2. Trends and Future Work Perspectives

The last aspects to be analyzed in the literature are the trends and future work perspectives. Many innovative technologies and techniques have emerged in the last years regarding EVs and buildings and are being increasingly studied by researchers in the field. This section presents some of the trends identified in the literature collection hereby approached. The first trend and the most mentioned in this work is V2G, which, as already mentioned, allows the EV to work as a mobile storage system and a full-time energy support system for houses and buildings. However, it is important to consider that, as mentioned above, more chargers are needed to make full use of the V2G capabilities, with attention to bi-directional chargers. Moreover, EVs also must have bi-directional capabilities, and currently, the variety of models with such technology is extremely limited. In this sense, there is no doubt that this will be one of the most promising trends of the future.

Allied with such disruptive features, transactive energy (TE) markets between EVs and buildings are also a trend [96,97]. Thanks to V2G technology, it is already possible for these entities to commercialize electricity between one another (as seen in some references mentioned earlier). As this reality is still in an early phase of development, it is expected that more research will be conducted in this sector in the future. A practical example is Ref. [98], where the authors reviewed how smart buildings can provide services to the grid through a TE framework, as well as the related opportunities and challenges. Additionally, it is expected that specific policies will be created to stimulate its adoption on a large scale and to promote fair competition with other market models. It is important to understand that the generated electricity can be traded via TE either at an individual level (e.g., between the building and the individuals who use it, such as students, employers, or customers) or at a community level (in a determined area and, mainly, between the members of the community), or even both, being a complementary technology for the energy communities concept that will be shortly explained.

Inside the TE market trend, two new technologies are gaining attention as transaction methods. The first one is known as blockchain, which, by the use of PV surplus, allows charging transactions to be carried out with better security of information provided by the parties and with a more competitive price than the price offered in the retail market. Additionally, blockchain alleviates the grid load and improves the reliability of the system. The authors of [99] proposed a business model using blockchain where payments were made via a mobile app. The second emerging technology is peer-to-peer (P2P), an energy trading method that allows prosumers of a community or cluster to trade surplus energy with each other, increasing their benefits and consumer benefits [100]. As with blockchain, P2P also reduced the load of the grid while improving the reliability of the system and reducing operational and maintenance costs. A practical business model using P2P was presented by [101].

The last identified trend and probably the most promising of all is the energy communities concept. This idea considers that multiple stakeholders of a community or a cluster (such as houses, buildings, EVs, etc.) can interact with each other in a way that makes it possible to trade electricity without the need for a grid operator, achieving self-sufficiency in energy generation and commercializing the surplus generation to the community. As a payment method, TE can be used to ensure safe and competitive transactions. Recently, the European Council and Parliament published the Regulation (EU) 2019/944 [102], in which the development of energy communities is promoted; this regulation also proposes rules for an improved market design in the EU. This trend was already mentioned by [43] and is also indirectly referred to in Refs. [61,66] through the suggestion of expanding the proposed model to neighborhood/district levels and scenarios with multiple PBs, respectively. Regarding the EVs, they will act as a mobile storage energy system (as already seen in [15,16]) and a service provider when the surplus is insufficient to meet the loads. This concept will have a major impact all over the world, with particular attention on islands and remote regions, where access to electricity is much more limited or even nonexistent.

5. Conclusions

EVs and buildings with smart energy management tools are trends that are already part of our daily lives, and their widespread integration towards a more stable and resilient electrical grid has already begun. It was seen that EVs can contribute towards a more stable grid, a higher degree of matching between local electricity generation and demand, and improvements in energy consumption efficiency beyond reductions in operational costs and GHG emissions, for example. Many different tools and strategies can be used to optimize such innovation, and multiple factors must be considered for its successful integration. However, no studies regarding the full integration of EVs and buildings thoroughly explored the strategies, limitations and future trends regarding the subject presented at an individual level, demanding contributions that approach these aspects in one single framework. In this sense, this work presented a systematic review of the optimization techniques applied for the integration of EVs and PBs, and a review emphasizing PBs was developed. Furthermore, an integrated picture of the constraints, as well as future trends and perspectives, regarding the integration of EVs and PBs was presented. The study also contributes an understanding of the incentives to create new policies that will allow the wider dissemination of this integration. First, the methodology used to produce this research was the Lens [47] open-access platform, which, due to its large availability of sources and statistical parameters available, allowed us to assess the evolution of scientific contributions in terms of the number of publications in recent years (with a time frame from 2012 to 2022) and the most studied areas in the same time frame. In total, 743 publications were found using two strings ("Electric AND Vehicles AND Public Buildings" and "Electric AND Vehicles AND Public Buildings AND Review") and were later selected for analysis according to the title, abstract, and relevance to the study. As limitations, the conducted analysis did not make use of other approaches such as bibliometric analysis [103] or even a combination of systematic and bibliometric reviews [104], nor did it use other filters such as country of publication, citation count, etc. It was noticed that, although there was a decrease in the amount of produced content between 2020 and 2022, the tendency is that the number of articles published on this topic grows every year. Next, a collection of findings was presented, analyzing in more detail the publications that were more aligned with this work, organized by applied technique (MO, ML, and both in some cases). Later, a global perspective of the literature was presented, where the findings were organized by reference number, perspective, applied methodology, optimization objectives, and findings/constraints.

Then, a discussion of the literature was performed, identifying the contributions of the global picture and the constraints pointed out by the authors (classified as technical and economic). Regarding their contributions, EVs are major contributors to a more resilient and efficient power grid, being capable of working as mobile storage systems and flexible resources to support local PV generation. Although important advances have already been achieved (V2B2 technology, BES, the combined application of MO and ML techniques, and the integration of EVs and PBs with DG resources), more research must be carried out to explore their full capacities. The constraints that were most identified in the literature are technical and economic, with special attention to battery degradation, uncertainties regarding the driving schedules of the drivers of the vehicles, electricity tariffs, and charging infrastructure. In addition, the trends and future perspectives and policies were also presented, with the most promising being V2G, TEs, and energy communities.

Finally, in future work, further research could be carried out using bibliometric analysis or other approaches, or even a combination of two different techniques. Additionally, studies involving the development of new strategies and policies/regulations focused on the dissemination of PBs with mounted solar panels with integrated charging stations for EVs will be major contributors. With these conclusions, this work provided a global perspective of what already has been achieved in the field of integration between EVs and PBs and the areas that will play a major role towards achieving a decarbonized society.

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