

Review

Planning of High-Power Charging Stations for Electric Vehicles: A Review

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Abstract: Electrification of mobility is paving the way in decreasing emissions from the transport sector; nevertheless, to achieve a more sustainable and inclusive transport system, effective and long-term planning of electric vehicles charging infrastructure will be crucial. Developing an infrastructure that supports the substitution of the internal combustion engine and societal needs is no easy feat; different modes of transport and networks require specific analyses to match the requirements of the users and the capabilities of the power grid. In order to outline best practices and guidelines for a cost-effective and holistic charging infrastructure planning process, the authors have evaluated all the aspects and factors along the charging infrastructure planning cycle, analysing different methodological approaches from scientific literature over the last few years. The review starts with target identification (including transport networks, modes of transport, charging technologies implemented, and candidate sites), second, the data acquisition process (detailing data types sources and data processing), and finally, modelling, allocation, and sizing methodologies. The investigation results in a decision support tool to plan high-power charging infrastructure for electric vehicles, taking into account the interests of all the stakeholders involved in the infrastructure investment and the mobility value chain (distributed system operators, final users, and service providers).

Keywords: charging infrastructure; planning; electric vehicles (EV); high-power charging (HPC); high-power charging station (HPCS); transport models; load profiles; grid models; decision support



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1. Introduction

Electrification of the transport sector is a key and necessary step for achieving the goals of the Paris Agreement and for avoiding the worst consequences of climate change, such as the loss of environmental habitats and the disruption of ecosystems. In the past decade, the need for a sustainable transport system has been raised by civil society and policies.

One of the promising strategies to abate emissions from transportation is a rapid substitution of internal-combustion-engine vehicle (ICEV) fleets with electricity-based alternatives. Industry trends are enhancing the electrification process: for example, the cost of batteries will drop below 150 €/kWh by 2025, which means that the electric vehicle (EV) will reach cost parity with ICEV in the next few years [1]. Currently, the spread of charging stations is mostly headed by charging companies, which compete against each other and allocate chargers with a low level of interaction with other actors, such as the distribution system operator (DSO) and without much input from city central planners and regional or national authorities. Moreover, the site selection model of existing charging stations was built through a static viewpoint [2], which placed charging stations to supply a certain share of current mobility patterns. However, charging infrastructure (CI) should be allocated and sized with a long-term planning perspective. Stations installed today should be running cost-effectively in future scenarios, and have no need for reconstruction or relocation due

to significant changes in mobility patterns or grid expansions imposed by the electrical infrastructure. Long-term planning can therefore increase the chances that the infrastructure will be adequate for future electric mobility while efficiently capitalizing on it. In this regard, predicting transportation demand is an important and necessary parameter for providing EV users with the electrical supply they need, when they need it.

CI planning requires the identification of the transport network type to be electrified in order to take into account the different characteristics and needs of drivers. Authors in [3] distinguish between two categories of charging demand types: inter-city and intra-city demand. The former refers to a charging need that must be met during a break in a long-distance journey, whereas the latter refers to a charging need that must be met at the end of a short-distance trip, thereby making use of parking time to charge the EV.

Urban networks are characterized by intra-city demands: most EV urban users start charging cycles at the end of short trips. In urban environments, trends such as a rise in active mobility (walking and cycling) are likely to affect mobility patterns. Long-term planning must consider these potential trends, and scenario planning could support decision-makers in this process [4]. Moreover, characterizing and predicting mobility scenarios requires analyzing a wide range of parameters, such as the vehicle-to-refuelling index (VRI) (numbers of EVs divided by number of chargers), which can give planners a basis for evaluating further investments in public charging assets. At the same time, cities with different characteristics will have to invest differently. For example, the availability of private parking with slow, overnight chargers influences the number of public chargers that should be planned. Instead, the electrification of inter-city travels requires investments in fast charging stations (FCSs) along routes in order to complete the trips.

Considerable care must be taken when considering the ratio between fast- and slow-charging points: the optimal ratio has to be carefully estimated and assess the needs of the current system, answering questions like:

- Is there a need for en-route fast charging?
- Would the uptake of EVs benefit from more fast chargers?

Furthermore, different charging technologies are being developed, ranging from static plug-in charging to dynamic technologies such as inductive and catenary charging. Depending on the use case, a particular technology can be more or less suitable for the charging process and achieve better results in terms of economic benefits. Another question that arises is: what type of vehicles should the CI serve in the long term? In the Paris Declaration on Electromobility, international parties recognized the need to electrify at least 20% of all road transport vehicles by 2030 [5], and many cities are setting ambitious targets of a modal shift from private passenger cars to sustainable modes: the Mayor of London's Transport Strategy aims for 80% of all journeys to be made by walking, cycling, or public transit by 2041 [6], whereas as of 2019 in Buenos Aires, only 14% of journeys are made with private motorized transport [4]. CI should therefore anticipate and accelerate a modal shift to reduce the overall ecological footprint of the traffic sector, rather than limiting the planning process for the exclusive use of passenger vehicles.

Finally, the problem of allocating charging stations (CSs) can be reduced in its complexity by pre-selecting candidate sites where costs (such as land, grid connection) can be minimized and coverage of main traffic flows can be maximized. All in all, the need to provide final users with a CI that can supply energy to the EV fleet without compromising grid stability is crucial for the future of both transportation and electrical system planning. Increasing demand for motorized vehicles, coupled with the expanding economic capacity of society, will further enlarge the size of private vehicle fleets, which is expected to have tripled by 2050 compared to 2000 [7]. This growth has created social, environmental, and health issues, such as traffic congestion, air and noise pollution, greenhouse gas emissions, accidents, and physical inactivity among users. All of these factors are adverse to society in terms of costs, economic productivity, and environmental externalities [8]. A holistic spectrum of areas has been studied in order to mitigate losses derived from these factors and enhance the sustainability of the transport sector, including use of technology, infras-

structure expansion, incentives for driving behavioural changes, limitations of car traffic, and aggressive land use policies [9]. The adoption of electric cars together with the CI planning can be described as a “chicken-egg dilemma”, as pointed out by authors in [10]: replacing a fossil fuel-based mobility with an electric one is intrinsically connected to the CI that can enhance the transition in a mutual positive feedback-loop, as visualized in Figure 1. The negative drawback is that the lack of one element (either EV uptake or CI) can potentially hamper the loop, resulting in a situation of stall.

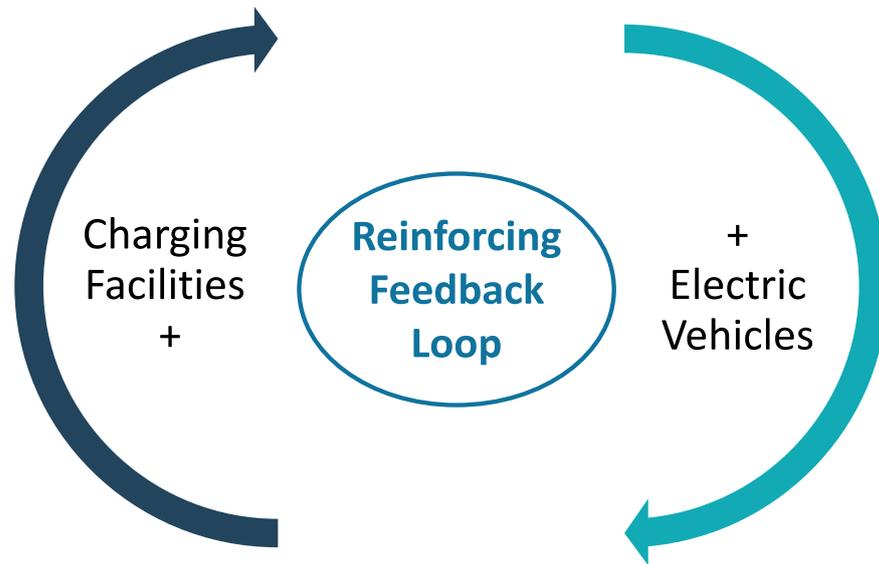


Figure 1. Feedback loop between EV uptake and charging facilities development.

Several authors investigated the level of development of the CI in order to better plan future actions and investments. In their literature review, authors in [11] found that approximately 10 optimally located fast chargers are sufficient for every 1000 EVs, but were unable to draw general conclusions based on the small amount of studies that were reviewed. It has since been found by [12] that 0.3–1.8 fast chargers per 1000 EVs are suitable, much like the VRI used for combustion engines. It was shown that 314 optimally located FCSs would be sufficient for serving the European highway network (0.7 per 1000 in Germany) [13] and 250 FCSs in the US highway network [14]. As stated by [12], this seems inconsistent, as more chargers are already currently available than this theoretical number. However, several empirical studies indicate similar results. A partial conclusion that could be drawn is that more efforts are needed in order to optimally locate and size charging stations, thereby increasing their utilization rate.

So far, CI has mainly been developed for road vehicles, but in recent years, maritime transport has also started to take its first steps in the electrification transition. The first battery-electric ferry was put into operation in Norway in 2015 [15], and in 2017, the world’s largest inductive charger was installed for high-power ferry charging in Norway at 1.2 MW [16]. Electrifying ships for long-distance travel is more challenging due to the battery size required. However, hybrid solutions are becoming popular for reducing local emissions in ports and fjords [17]. Passenger vessels in particular seem to be moving towards decarbonisation, whereas cargo ships only implement small hybrid solutions [18]. In Tallinn’s Old City Harbour, ABB installed an 11 kV charger for vessels in the context of a European project involving Estonia and Finland. Moreover, in 2016 the Port of Tallinn, Port of Helsinki, Port of Stockholm, and Port of Turku signed a memorandum to develop shore power facilities with a common standard [19].

Contributions and Structure

The issue of CI planning has been thoroughly examined in literature on the application of both transportation and power system research in order to articulate a comprehensive and holistic solution. The novel contributions of this review include:

- An extensive, state-of-the-art review of the literature concerning the planning of charging infrastructure for EVs;
- An in-depth categorization of studies analyzing which factors are important for different electrification targets;
- An overview of state-of-the-art methods for optimal sizing and allocation of high-power charging stations (HPCSs).

This review aims to approach the CI problem in all its successive steps: the target identification, the data acquisition, and the planning. Initially, this review was approached by using combinations of the following terms: “planning”, “allocation and sizing”, “charging infrastructure”, and “fast charging station”. However, from the first iteration of research, it was clear that the majority of the literature focused on passenger vehicles and urban transport networks. Therefore, specific terms such as “electric ship”, “shared mobility”, “trucks”, “inductive charging”, or “highway” were included and combined with former ones in order to comprehensively represent all the categories of interest of this review. The structure of the review reflects the planning process, which is demonstrated in Figure 2. Section 2 thoroughly categorizes the main factors that must be identified when stating and circumscribing the problem: which transport networks are considered, which type of vehicle the study focuses on, which charging technologies are implemented, etc. Section 3 outlines the approaches taken to the collection and use of data. Section 4 outlines the methodologies for modelling and planning CI and highlights geospatial analysis procedures and optimization methods. Given the vast amount of literature focusing on optimization approaches, these have been further described in Section 4.2, with an in-depth explanation of different stakeholders’ viewpoints.

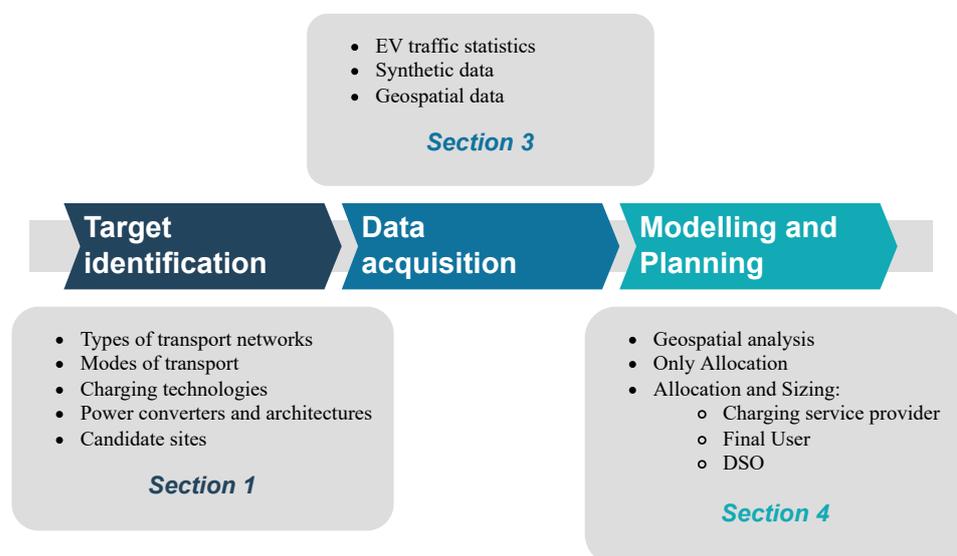


Figure 2. Structure of the review paper.

The benefits and impacts of sustainable mobility planning are described in Section 5, including their social, economic, and environmental impact. Finally, Section 7 outlines identified research needs, and discusses main research outcomes. For the purpose of this paper, the term *High Power Charging Station* (HPCS) will be used in order to consider the impact that several chargers operating simultaneously can have on the grid. This term is used to refer to a station with an aggregated power level higher than 30 kW. The term *electric vehicle* (EV) has been used in various ways throughout the literature, and it is usually

used to denote electric cars. This causes confusion when reviewing literature. Therefore, it is the opinion of the authors of this paper that (EV) should be used consistently as a general term to cover all modes of transport with an electric propulsion system and have used it accordingly.

2. Target Identification

Due to the complexity of the problem, planners should identify and characterize several aspects when defining their electrification strategy. In this section, the scope and objectives of the CI planning process are described:

- What type of transport network is considered?
- Which modes of transport are included in the electrification strategy and which ones are neglected?
- Which charging technologies are implemented in the CI?
- Where and how are the candidate sites for CI selected?

Furthermore, it is particularly important to account for changes in mobility patterns and to define the planning time-horizon and whether the CI is intended for private or public transportation. From Table 1, it can be concluded that recent scientific papers focused on planning CI to supply the private fleet, with the purpose of replacing the ICEV fleet with electrical alternatives.

Table 1. Time horizon in literature for planning charging stations.

Time Horizon [yrs]	Private	Public
≥ 5	[20,21]	
$\geq 5 \wedge \leq 10$	[22–24]	[25]
$\geq 10 \wedge \leq 15$	[23–28]	
≥ 15	[29–31]	[32]

In the following sections, current literature is analyzed in order to present how the different aspects of the planning problem have been defined.

2.1. Types of Transport Networks

For the purpose of this review, studies have been categorized according to the type of transport network considered in the allocation and sizing (AS) process.

2.1.1. Urban

As indicated in Table 2, the reviewed literature focuses strongly on urban areas, which is in line with rising trends of urbanization worldwide. This literature review shows that urban planning of CI is generally approached from the perspective of a central urban planner. In addition, not many studies considered home charging in their resolution. In their survey [33], the authors assessed that charging stations in urban contexts are mainly placed according to objectives such as reducing grid loss and predicting the expected charging demand. Study [34] focuses on fast CI planning in the city of Chicago. The authors state that predicting fast-charging demand is more difficult compared to slow-charging, as time availability and deviation from the driver's route must be considered in order to ensure a high quality of the service offered. Results from the EV project show that state of charge (SOC) is nearly always above 78% after home, slow-charging events [35], and the authors in [36] use data from the National Household Travel Survey to demonstrate that home charging constitutes the largest share of power demand, especially during the late evening. More recent statistics are needed in order to quantify the impact of home charging on meeting EV charging demand. However, ref. [36] assesses that an increase in public charger network coverage would impact driver charging behavior: 20% of charging events at public stations could account for up to 40% of total electricity demand thanks to DC fast chargers.

Table 2. Target identification.

Ref	Approach		Allocation and Sizing	Transport Network					Mode of Transport				HPCS	Candidate Site
	D	M		U	R	I	H	P	B	T	S	HDV		
[20]		✓	✓	✓				✓					✓	✓
[21]		✓	✓				✓	✓					✓	✓
[22]	✓		✓	✓				✓					✓	
[23]		✓	✓	✓				✓					✓	✓
[24]		✓	✓	✓				✓					✓	✓
[25]		✓	✓	✓				✓	✓				✓	✓
[27]		✓	✓	✓				✓					✓	
[28]		✓	✓	✓				✓					✓	
[29]		✓				✓		✓					✓	✓
[30]		✓	✓			✓		✓					✓	✓
[32]		✓	✓	✓					✓				✓	✓
[34]	✓		✓	✓				✓		✓			✓	✓
[37]	✓			✓	✓	✓		✓			✓		✓	✓
[38]	✓		✓			✓		✓					✓	✓
[39]	✓					✓			✓				✓	✓
[40]	✓		✓				✓	✓					✓	✓
[41]		✓							✓			✓		✓
[42]	✓		✓	✓					✓			✓		✓
[43]	✓		✓	✓					✓				✓	✓
[44]	✓		✓	✓					✓				✓	✓
[45]	✓			✓						✓			✓	✓
[46]	✓		✓	✓						✓			✓	✓
[47]	✓		✓			✓						✓	✓	✓
[48]	✓		✓								✓		✓	✓
[49]	✓		✓	✓							✓		✓	✓
[50]	✓		✓	✓				✓					✓	✓
[51]		✓						✓		✓			✓	
[52]	✓		✓	✓				✓					✓	✓
[53]		✓	✓					✓					✓	✓
[54]	✓		✓				✓	✓					✓	✓
[55]	✓		✓	✓				✓					✓	✓
[56]	✓		✓					✓					✓	✓
[57]	✓			✓					✓				✓	✓
[58]		✓	✓	✓				✓					✓	✓
[59]		✓	✓	✓				✓					✓	✓
[60]	✓		✓	✓				✓					✓	✓
[61]		✓	✓	✓				✓					✓	✓
[62]		✓	✓					✓					✓	
[63]		✓		✓				✓					✓	✓
[64]	✓			✓				✓						✓
[65]		✓	✓					✓						✓
[66]	✓			✓				✓						✓
[67]		✓	✓	✓				✓						✓

Approach: D (data driven), M (model driven); Transport Network: U (urban), R (rural), I (inter-city), H (highway); Mode of Transport: P (private), B (bus), T (taxi), S (shared), HDV (heavy-duty vehicles).

2.1.2. Rural

Study [37] is the only study reviewed that allocated CSs in a rural area (Alto Adige, Italy) while comprehensively presenting implementation for highways and urban networks. In this report, authors discuss several challenges of the allocation problem from two different geographical perspectives: cities and rural areas/highways, highlighting the main differences. The authors suggest that city-level allocation requires electric power distribution network input, public transport stations, and residential statistics. The problem for rural/highway networks is solved through the use of an algorithm to compare all network distances between them. In contrast, ref. [68] predicts the number of slow and fast CSs using a simple mathematical model based on the daily charging demand of EVs for

the entire US territory that also considers rural areas. The results show that the number of estimated slow charging stations (SCSs) is five times larger than FCSs throughout the country.

2.1.3. Inter-City

Inter-city allocation of CSs has been the subject of more investigations than rural allocation, and the literature highlights how greater distances (compared to inner-city traffic) can differentiate the methodology of resolution. Inter-city articles assess a broader use of FCSs due to time constraints and larger charging demands. For example, in [30], the use of FCSs is applied to 5000 traffic zones in California, including more than 480 different municipalities. Charging demand is modeled in terms of traffic flow rate (vehicles/hour), using queuing theories to simulate stochastic charging activities. The model considers three five-year planning stages, and paths are selected in order to be feasible for each O-D pair in all stages. In [38], 100 kW up to 200 kW chargers are implemented in central Ohio using the shortest path model. Charging demand is estimated by also analyzing the average vehicle speed data for all road segments in the network dataset. Authors in [39] investigate the optimal allocation of FCSs for electrical buses, taking into account inter-city routes between Salt Lake City, Park City, Provo, Ogden, and Tooele.

2.1.4. Highways

Finally, a few articles specifically analyzed the problem for highways. In order to differentiate them from inter-city networks, studies in Table 2 are only categorized under this class when highways are explicitly included in transport models. In [21], FCSs are implemented on a round highway, using the topology of the road network of Hainan Island, China. The model includes a Monte Carlo simulation to randomly generate initial SOC and charging anxiety (SOC at which it becomes necessary for the user to recharge). Geographic information is coupled with a statistical survey of EV fleets (number of vehicles and departure times). Finally, ref. [40] formulates a detailed resolution methodology for AS of fast charging station (FCS)s, which is applied along the entire Italian highway network in [26], thereby producing an estimation of FCSs for different scenarios and for each region of the country.

2.2. Modes of Transport

A fundamental distinction between deterministic and probabilistic vehicles can be made for all types of vehicles:

- Deterministic vehicles are the ones for which the route, time of departure, and time of arrival are known beforehand. Electrification of these vehicles means that it is possible to predict where the charging cycle takes place and characterize the charging demand with small error (in terms of energy and power). Buses and ferries are examples of deterministic vehicles.
- Probabilistic vehicles include vehicles for which route and time of departure and arrival do not follow a fixed routine or schedule. To calculate charging demand of probabilistic electric vehicles, probabilistic models (such as Monte Carlo simulations) need to be applied in order to consider the random behaviour of users. Electric passenger cars and bicycles are examples of probabilistic vehicles.

2.2.1. Passenger Vehicles

Scientific literature demonstrates a clear interest in the study of passenger vehicle CI, which can be observed from Table 2; almost three-quarters of analyzed articles include this private mode of transport, and the other reviews confirm this research focus [69].

2.2.2. Buses

The second type of vehicle that research focuses on is buses. Electrification of this mode of transport may be of interest to public entities or companies running public trans-

portation services, as it can reduce the vehicle's operational costs and environmental footprint. Compared to light-duty vehicles (LDVs), battery electric buses (BEBs) violations of schedules and/or paths are generally more costly [70] and usually characterized by pre-specified duration constraints [41]. In addition, given the fact that buses are required to operate up to 16 h per day, compared to just 1 h for LDVs [71], en-route fast-charging stations are a necessity, as are higher power capabilities [42]. As described in [72], several charging strategies can be implemented specifically for buses: conductive charging through pantograph charging or overnight depot charging are some of the most innovative and favorable options for buses operating in urban areas. Of the literature reviewed concerning AS, only one study includes both private and public transport [25]. In this case, the authors investigate the use of centralised charging coupled with battery swapping to supply both private electric vehicles (EVs) and buses, analyzing the statistical data of moving daily distances. In all other cases, the problem is examined solely for EVs, probably due to the above-noted differences that exist. Several articles investigate the conversion of bus fleets from using conventional fuels to electricity in urban contexts. In their case study analyzing the transit network of Davis, authors in [43] conclude that it is not only more environmentally friendly to utilize electric buses, but also economically more beneficial compared to ICEV. In [42], authors find that of 143 bus routes, 42 can be electrified in a cost-optimal way for the city of Stockholm. The resolution process uses ArcGIS to analyze the length of each route and produce an optimal set of FCSs for en-route charging. Furthermore, in [39], authors aim to minimize the cost of replacing a certain number of conventional buses and also consider in-depot charging strategies. In this case, terminals are potential locations for en-route CSs and garages are potential locations for in-depot CSs. The authors of [44] also account for simultaneous optimization of bus battery size and allocation of two different FCS technologies along routes to bus stations. Finally, the authors of [69] state that scheduling and location planning for public transport should be further coupled as integrated problems, given their high inter-dependency.

2.2.3. Taxis

The conversion of the taxi fleet to electrical alternatives presents significant fuel cost advantages, as taxis are heavily driven, leading to shorter payback times. Moreover, taxis cannot generally benefit from slow charging, as they operate 24/7. Therefore, their charging demand has to be supplied during the intermediate waiting time [45]. In [46], the case for Changsha, China is modeled, wherein authors analyze the GPS trajectories of almost 8000 taxis, stressing factors such as arrival rates, locations, and time of dwelling. The results show that offering waiting spaces where taxi drivers can dwell before charging can increase the utilization of chargers and reduce the number of chargers by up to 26%, although no cost-benefit analysis supports this. Another limit of the study is that queuing the model does not consider arrival SOC, which has a strong influence on overall waiting times. In [45], authors use real data from 6.3 million taxi trips in the city of Vienna to allocate FCSs solely for taxi use. This allocation does not produce an exact location, but hexagon-shaped cells in which is more convenient to install the stations. Moreover, no cost analysis is developed, and the number of CSs to be installed is set as a parameter, whereas the optimization maximizes charging demand satisfaction.

2.2.4. Heavy-Duty Vehicles

For battery sizes that range from 300 kWh to 1 MWh, charging time is and will be a major obstacle to the electrification of heavy-duty vehicles (HDVs). Few studies were found on how to plan CI for this mode of transport. Study [47] analyses the electrification of trucks deployed for port logistics in southern California. The authors affirm that, at the time of writing, no other best practice models exist for siting heavy duty charging stations. The results show that a considerable part of the logistics fleet can be substituted with respect to grid capacity. Stations should be located at truck yards, with overnight charging meeting most truck charging needs. Study [41] describes how locomotive refueling models can be

used to capture the charging demand of vehicles' charging duration constraints, such as buses and vehicles deployed in logistics companies. The study suggests an allocation of CSs and a schedule of the optimal vehicle recharging strategy that minimizes total costs while meeting the needs of the contracted delivery of freight or people to be transported.

2.2.5. Autonomous and Shared Vehicles Fleet

Very few articles were found to investigate how the CI can be planned for free-floating car-sharing systems and autonomous vehicles. Study [48] comprises a recent and comprehensive body of academic work of AS of FCSs, using historical data of a shared EV fleet that is already operating in the city of Seattle. In this study, total downtime is minimized by providing the optimal schedule for charging operations as well, but authors do not consider cost in the objective function. Moreover, the future charging demand is roughly estimated, with no reference to market trends or user acceptability. In contrast, study [49] makes use of historical green taxi trip records in New York City to locate Level 2 CSs for a car-sharing fleet in Brooklyn. Authors comprehensively optimize the size of the fleet, its management, and siting and sizing the charging stations in order to minimize the total costs, but they do not consider the electrical power network in their decision process. Finally, study [73] proposes a joint model that includes interactions between electric power networks and autonomous, mobility-on-demand transport systems, including V2G schemes. The model calculates complete operations for the autonomous fleet, from routing cars to complete trips, on request and controlling empty cars in order to distribute them according to the trip demand. The authors show that coordination between power and transport systems can even decrease electricity prices, despite the higher demand, whereas absence of coordination can result in significant price increases and widespread blackouts.

2.2.6. Ships

Only a few studies analyze the traffic load of ships, and none of them resulted in the design of a CI. The authors of [74] analyze the routes and operational activities of eight ship types to identify which ones can benefit the most from hybrid or electric propulsion. The authors of [75] explore how cold ironing could be a potential green-powering solution for ports in the short term and show the design of two shore supply connection points in the port of Killini (Greece) as well as further possibilities for coupling the system with a hybrid design. Apart from solar- and wind-based generators, the authors highlight the importance of a battery storage system in the port to maximize renewable energy consumption and serve as an energy buffer within the main grid.

2.3. Charging Technologies

2.3.1. Plug-in Charging

Plug-in charging is the most mature charging technology and the most present in global CI, with more than 5 million units between private and publicly available chargers [76]. Chargers are characterized by:

- Level: the power output of the outlet.

There are three commercially widespread levels. Level 1 (up to 3.7 kW) and Level 2 (up to 22 kW) exploit AC current, whereas Level 3 can be either AC or DC. Level 3 chargers are referred to as fast chargers, and the power outputs range from up to 43.5 kW for AC 3-phase technology to up to 400 kW for DC [77,78]. Currently, standards for high-power chargers have been developed up to 600 kW, with a growing interest in so-called *mega-chargers* up to 1 MW [76] for HDVs.

- Type: socket, connector, and standards.

Charging stations are developed based on different standards and defined by the Society of Automotive Engineers (SAE), a U.S. based professional association, which develops standards for engineering bodies in different industries. The International Electro Technical Commission IEC 61851 and American standard SAEJ1772 represent the two main

standards defining the communication protocol and electrical and physical parameters [79]. A brief selection of important standards for charging stations is reported in Table 3. For further relevant standards, see [79,80].

Table 3. Relevant standards for charging stations [79,80].

Standard	Scope
SAE J1772	Discusses all the equipment ratings for EV charging including circuit breaker current rating, charging voltage rating.
SAE J2293	Establishes the requirement of on and offboard charging equipment.
SAE J2847	Provides standard communication requirements between the utility grid and plug-in electric vehicles.
SAE J2954	Defines a wireless power transfer of all types of plug-in electric vehicles and coil alignment methodology.
IEEE 1547	Defines standards for interconnecting distributed resources with electric power systems.
IEC 61980-3	Defines the magnetic field-based wireless power system and its specific requirements.
IEC TS 62840-1	Gives a general overview for battery swap systems.
IEC 61851-21-1	Defines requirements for conductive connection of an electric vehicle (EV) to an AC or DC supply.
IEC 61851-24	Defines a digital communication between a DC charging station and an EV.
IEC 62196-1	Gives a general overview of the interface between the EV and the charging station.
IEC 62196-2	Extends the previous designs with detailed description of plugs and socket outlets.
IEC 62196-3	Describes the DC vehicle coupler and defines the characteristics of the DC vehicle coupler.

Types of sockets and connectors adopted in the different countries may vary. The European Union mostly follows the Type 2 IEC 62196-2 and Type 2 IEC 62196-3 standards, also commercially called Combined Charging System Combo 2. The most common DC fast charger plugs in the global market are the CHAdeMO (accepted by IEC 62196-3), the Tesla supercharger, and the Guobiao recommended-standard 20234 [76].

- Mode: the communication protocol.

Different chargers host different types of communication protocols. Whereas AC slow-chargers have no direct communication in their cables, it is possible to regulate the charging speed of AC fast-chargers, but it still require external controls for communication. In contrast, DC fast-charging CCS is coupled with power line communication (PLC), whereas CHAdeMO, Tesla, and Guobiao use a controller area network (CAN). PLC and CAN protocols allow for smart charging strategies such as V2G [76]. In the reviewed literature, authors do not always specify the complete characteristics of their chargers, and some of them describe chargers depending on the nominal power output or the time taken to complete a full charge of an average BEV [81].

A fair amount of research investigates infrastructure planning, taking into account both fast and slow charging. Study [82] analyzes the effect of implementing Level 1 (1.9 kW), Level 2 (4 kW), and Level 3 (up to 100 kW) chargers on the voltage profile of a power system. The authors verify that the critical voltage drop in commercial feeders can be remarkably reduced through the optimization described in the paper, even with a high penetration of Level 3 chargers. A similar range of charging powers is included in [50,81]. In [50], technologies compete against each other in a Bayesian game model, each of them implementing one different charging technology. The overall consumer satisfaction is finally characterized to prioritize EV user satisfaction. Results indicate a small presence of DC FCSs in the optimal solution (ca. half of Level 1). In [51], the authors

optimize the number and size of chargers based on slow and fast chargers, including ADC type, as well as chargers that can shift between slow and fast charging modes. Study [46] allocates and sizes chargers between AC Level 2 (20 kW) or DCFC (80 kW), whereas [83] calculates the charging capacity of low voltage networks for both single-phase 3.7 slow and three-phase 11.7 kW chargers. A unique case is considered in [84], a recent study in which wireless solutions are implemented together with DC fast charging and AC Level 2 charging. However, no analysis is made to assess which technology brings the highest benefits.

2.3.2. Battery Swapping

The Battery Swapping Station (BSS) is designed to provide the customer with a charged battery. It was initially adopted to supply public transport [85] and is now only implemented in Asian countries [76]. Large-scale implementation of battery swapping presents several challenges, such as the absence of a standard for battery interfaces across EV manufacturers and user acceptance [86]. In the current mobility system dominated by passenger vehicles, these obstacles can hinder the use of this technology for most EVs. Moreover, the cost of setting up a BSS is up to 10 times higher compared to a FCS. Therefore, the range of spatial distribution is decreased for the same budget [87]. The use of battery swapping can be better suited for vehicle fleets: in [88], long-term planning for electric taxis shows that BSSs are economically better than plug-in charging. Nevertheless, the fluid operation of an EV fleet requires a large stock of batteries, which means investors face large, upfront costs in the first phase of implementation. A useful cost-benefit comparison is provided in [52] on the allocation of both fast plug-in and BSSs in Shenzhen, China. A Pareto analysis shows a higher presence of plug-in stations if short-term economic benefits are prioritized, whereas implementation of BSSs results in a higher quality of the service provided to the final user. In addition, the load generated by plug-in technology can result in more severe peaks than battery swapping, as shown in [89]. Furthermore, BSSs can decrease the battery degradation through a slow charging process. Allocation and sizing of BSSs are also modeled in [25], where each station can be assigned no more than eight chargers that can operate simultaneously, each one with 5 kW of rated power. Study [90] compares different technologies in a long-term plan in Daegu, South Korea. The authors analyze plug-in, inductive, and battery swapping technology, and conclude that battery swapping is economically more beneficial for single and composite routes.

2.3.3. Inductive Charging

The operational principle of inductive power transfer resembles the operation of conventional transformers. The general scheme includes a transmitting coil that generates the electromagnetic field, usually integrated in the street, and a coupled receiving pick-up mounted on the vehicle, which is finally followed by a rectifier. Due to the large air gap, a capacitor bank is usually included as well [91]. A pilot project in Germany demonstrated the operation of a 200 kW inductive power transfer for a HDV [92]. Very few authors consider wireless solutions for AS. The authors of [42] take into account both inductive (200 kW) and conductive charging (300 kW), and an upper limit of 5 min for charging time is imposed on the resolution process. Due to higher upfront costs of inductive charging, only conductive charging stations are implemented in the cost optimized solution. In [43], the authors make use of an automatic CI through an inductive overhead system but do not specify the characteristics of the charger. Wireless solutions present several characteristics that can increase user comfort compared to static charging and battery swapping, such as the possibility to charge the vehicle on the move (dynamic charging) and avoiding the use of connectors that must be plugged by the users. On the other side, researchers investigated whether the electric and magnetic field produced during the coupling could result in safety concerns for human health. In [93], the authors studied the coupling of a double coil and a unipolar coil to achieve the maximum coupling coefficient; researchers analyzed the operational risks for humans, concluding that worst case scenarios are well below International

Commission on Non-Ionizing Radiation Protection (ICNIRP) regulations. In [94], authors carried out a test in a laboratory facility (by a renowned automotive house) and verified an efficiency (DC power transmission) range between 86% and 90%. Recently, authors in [95] reviewed the technical characteristics of dynamic solutions implemented in pilots around the world. Researchers simulated the mobility demand of a highway in Norway (both for light and heavy duty vehicles) to ultimately design an electric infrastructure for both static and inductive charging infrastructures. In their results, the authors assessed the size of the conductors and the substations rating, comparing the load on the charging stations and on the substations.

2.3.4. Interoperability Issues

As observed in Section 2.3.1, there are many competing charging standards in use currently. The variety and incompatibility between these standards represent a barrier against an easy adoption of EV technology among vehicle owners: cross-border trips are currently virtually impossible, and integration of EV charging technologies to provide ancillary services to the power grid is jeopardized among different communication standards [96].

To summarize the problems in interoperability currently existing in electric mobility, the following can be highlighted [97]:

- Mismatch of the hardware interfaces;
- Multiple versions of different protocols covering the same communication link;
- Low level of standardization between high level actors.

The impact of the lack of interoperability can be described at different levels. In terms of user comfort, it has hindered the possibility of charging anywhere, across large areas; from an economic point of view, interoperability enables an easier maintenance of the charging infrastructure by avoiding potential conflicts in technology updates; finally, from a smart grid perspective, a low level of standardization between electric mobility companies (EV manufacturers, charging operators, etc.) and grid operators hinders the implementation of a scalable vehicle-to-grid infrastructure, and the full set of benefits that are foreseen in terms of integration of the electric transportation within the smart grid concept [98].

2.4. Power Converters and Architectures

The battery charger can be installed inside the vehicle (onboard) or externally (off-board). Both charging systems take AC power from the grid and convert it to the desired voltage level. Onboard battery chargers are limited in size, weight, and volume and are therefore suitable with Level 1 and Level 2 chargers. Onboard battery chargers operate from a single or three phase AC outlet and are typically capable of only unidirectional power transfer; however, in some configuration cases, bidirectional power transfer can be achieved [99]. Level 3 chargers, due to their capacity ratings, are typically installed outside the vehicle (offboard battery chargers) and operate on 3-phase AC power supply with higher power rating than onboard battery chargers. The external charging system is typically made up of two stages: an AC/DC converter that faces the connection point to the supply network, followed by a DC/DC converter that provides the DC interface to the EV charging system. These two stages typically allow bidirectional power flow [100]. In Figure 3, a schematic representation of most common charging system topologies for both onboard battery chargers and offboard battery chargers is shown.

The topology usually includes a first stage with alternating current–direct current (ac–dc) conversion that guarantees a sinusoidal grid current, and a second dc–dc conversion that ensures current and voltage on the EV battery, preserving the battery lifetime, in both onboard and offboard chargers. The rectifier stage can be performed by a half-bridge, full-bridge, or multilevel diode bridge, whereas the second stage is commonly performed by resonant power converters, because of the potential to achieve at the same time both higher switching frequency and lower switching losses [99]. An electromagnetic-interference (EMI) filter is responsible for maintaining the power quality on the power grid side [101].

The battery management system (BMS) ensures safety measures in the battery pack charging, both in terms of control and protection. Power control units implement the control algorithms, which can include PID controllers, fuzzy logic, and neural networks [102]. Finally, the protection is guaranteed through circuit interrupting devices (CID) and circuit breakers [100].

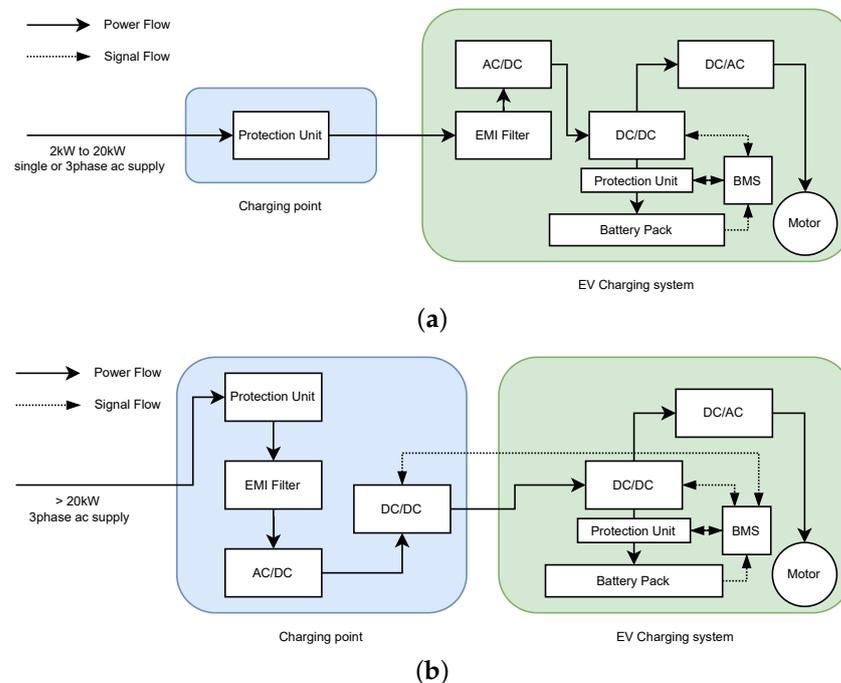


Figure 3. EV charging system topologies: (a) onboard charging, (b) offboard charging.

Based on the different battery charger typology adopted (level 1, level 2, or level 3), different architectures can be adopted in terms of common bus configuration. Two main categories can be identified, which are common AC-bus configuration and common DC-bus configuration. In AC-bus configuration (Figure 4a), an MV/LV transformer steps down the voltage from the main supply point, then a common AC bus feeds the EV charging stations and ancillary units, such as renewable energy source (RES)-fed power plants and storage units. The advantage of this configuration is a simple implementation as well as the possibility to feed generic appliances with low-voltage AC power. In a DC-bus configuration (Figure 4b), a single AC/DC rectification stage is connected directly downstream of the MV/LV transformer, and a common DC bus is distributed among the charging station appliances, such as charging stations and ancillary units. The main advantage of this configuration is the elimination of synchronization and reactive power issues [103].

A promising approach is represented by the utilization of solid state transformers (SST) (Figure 4c). This approach enables the direct connection to the MV line with the elimination of the LF transformer. It essentially covers the functionality of the LF transformer and AC/DC conversion stage with enhanced power density, with additional benefits in terms of bi-directional power flow, fault current limitation, and fault isolation [103]. An optimal design of energy storage units, renewable energy sources generation, charging stations, and support by energy management systems (EMS) is capable of ensuring different types of microgrid architectures, both in grid-connected and islanded modes, easily integrating distributed energy resources in the electric system [104]. Finally, several control strategies are proposed in the literature to ensure optimum operation at the EV-charging point [79,105].

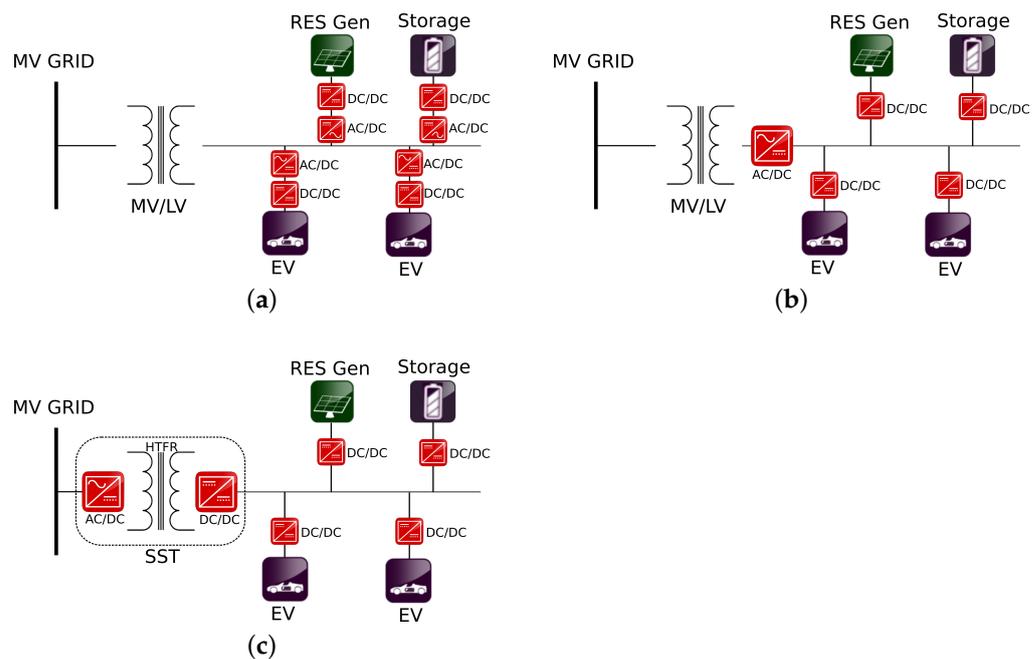


Figure 4. Charging station connection architecture: (a) common AC bus, (b) common DC bus, (c) solid state transformer.

2.5. Candidate Sites

Most of the investigated articles pre-select candidate sites that can be suitable for hosting charging stations. A large share of authors individuate traffic network nodes, such as road intersections or major transport hubs, as recommended options, wherein the allocation optimization or algorithm can evaluate the best set of sites [23,40,42,53,54]. Electric networks can also be considered. For example, in [22], the traffic system is superimposed on the electrical network topology, and intersections were used as possible FCS locations. Models that include a power flow analysis of the electric network usually site a load representing the charging station directly at low voltage buses ([82]). Other approaches are more complex than the ones described, as they involve spatially analysing the charging demand [21] or dwelling times [46,55]. For example, [56] applies a trajectory reduction procedure in order to reduce the traffic network to a set of candidate location points and finally weights the locations based on the mobility behavior of EV drivers. In [106], the authors use heat equations through a finite element analysis to produce heat maps for the cities of Boston and Milan. These analyses include parameters such as population density, routes, and electricity consumption. These approaches aim to individuate hot spots, which are places where it is more effective to locate a charging station (CS). In [48], the authors apply a clustering method, filtering only commercial urban zones and using origin charging demands points to create a set of contiguous clusters. Once these areas are obtained, the candidate locations are the centroids of the clusters. Instead, the authors of [28] do not indicate a specific location where to install a parking lot, but produce the optimal zones (cluster of buses) or the specific buses that correspond to which siting should be implemented. In [38], the authors point out that commercial retailers can be good candidates for siting FCSs, mainly because they likely have both the physical space and electrical infrastructure to install them. This thesis is also confirmed in [107]. CS candidate sites in literature usually include different points of interests (shopping centers, supermarkets, etc.) and public parking lots [40]. Finally, urban major transport hubs, bus depots, terminals, or bus stations are used as candidate sites in [32,42,44,57].

3. Data Acquisition

In this section, the types of data used in the planning process are analyzed.

3.1. Data Categories

Spatial- and time-dependent data can be categorized depending on the system they are describing:

- Transport network data: characterizes different aspects of transport infrastructures depending on the studies' application. This can include parking areas, existing gas stations, public transport stations, etc.

For this purpose, GIS data are used to map major intersections and road segments as in [38], patrol stations as in [66], as well as motorway exits [26] and highway junctions [29].

- Socio-economic data: including the type of neighborhood to be served (industrial, residential, etc.), GDP, EV ownership, etc.
- Electric system data: including geo-spatial data of the electric power system, the characteristics of the substations and the cabling, and the parameters that characterize the operations of the system. Modelling of the power system is implemented to assess the impacts of the charging demand on the distribution system.

Real networks are considered in few cases [108], whereas the majority of cases implement benchmark [109,110] or synthesized grids [111].

- Traffic data: extracted from GPS data to register the time of vehicles' successive positions or from stations that assess passing vehicles through a particular point of measurement. Origin–destination (O–D) data can also be used effectively when coupled with timestamps or even activity-based labelling of trips.

Traffic data are then analyzed to assess the mobility charging demand and ultimately the charging behaviour of users; this information is processed to extract the paths followed by vehicles, as in [34,52,112], or parking times [113]. In their review study, the authors in [114] differentiate between three categories of EV driving and charging data: surveys (such as the "Mobilität in Deutschland 2017", used in the recent study [115]), EVs trials, and charger trials. Charging behaviour can be analyzed from each of these sources, but a combination of two or all the categories results in the most accurate understanding of the phenomenon. Although GPS data were largely used in the reviewed literature, these input data can insufficiently represent complete mobility patterns of a population. Therefore, particular attention must be applied when using samples or creating new databases for studies. Finally, travel demand can be modelled through one-day or multi-day data, the latter being more accurate for reproducing travel needs [107], given the differences in mobility patterns between weekdays, weekends, seasonal variations, and festivities.

A small number of articles use accurate simulations to calculate the charging demand of EVs. In particular, the authors of [57] implement a discrete simulation event tool in MATLAB[®] in order to accurately estimate the energy consumption and downtime needed to charge and complete trips for a fleet of electric buses, taking into account stochastic events with a high level of precision (e.g., traffic lights). Instead, study [38] assesses the queuing probability through simulation in order to size the CI and ensure a contained queuing risk.

3.2. Model- and Data-Driven

Depending on the availability of the input data discussed in the previous section and the objective of the authors, the AS problem is formulated according to a model- or a data-driven approach [32,116]. The former, so-called "theoretical approach" implements mathematical modelling to capture the charging demand. The authors of [116] describe it as a procedure in which a mathematical methodology is coupled with synthetic data to produce AS of CSs. Studies fall in this category if they make use of real transport networks (distances, elevation profiles), but there are significant transport parameters for describing EV driving patterns (e.g., distance traveled) that are computer simulated or do not belong to the studied region/transport network. The model-driven approach is used in [58,59], wherein the authors apply random spatial distribution together with the Gaussian probability function to compute EVs arrivals. The authors of [58] scale EV arrival

curves depending on the population density of each neighbourhood. One of the parameters that is found to be commonly calculated through probabilistic methods is SOC. This is probably due to a lack of specific data regarding EV battery operational routines. In [61], the SOC of EVs arriving at charging stations have a normal distribution, whereas charging times (highly dependent on initial SOC) follow an exponential distribution in [117] and a log-normal distribution in [118,119]. Study [23] outlines a mobility scenario for building an FCS demand profile, wherein the authors make assumptions on the parameters of the study area (covered distances, number of cars present), the habits of the driver, and the features of the EVs fleet.

In contrast, “empirical” (or data-driven) approaches mainly make use of real-world data as a basis of the resolution process, and models are implemented in real case studies (e.g., the topology of real cities). Real data of probabilistic loads can be extracted from urban circulation datasets (real traffic zones measurements), EV ownership data, or EV user charging preference surveys. For example, in [82] the authors identify the best probabilistic distributions for describing arrival and departure times, plus the distance traveled, from a survey of 300 EV drivers. The data are also divided depending on the time of day (morning, evening, or night) and the type of feeder (residential or commercial) where the charging event takes place. In contrast, deterministic transport loads can make use of pre-existing timetable and routes. This is the case for [42], which evaluates 526 bus routes in the city of Stockholm, as well as for the city of Davis, which is investigated in [43]. The authors of [57] take into account six real express bus routes and proceed with accurate simulations in order to quantify the charging demand and travel time. Recently, the authors of [120] studied real charging patterns from several categories of charging sites (residential, office, car parks, and shopping centres). More than 80,000 real charging sessions were analyzed to assess the potential of vehicle aggregation to participate in ancillary services.

In conclusion, an approach based on a data-driven methodology allocates and sizes CI through accurate transport data. However, as stated in Section 1, a static approach to long-term predictions can lead to transportation scenarios that are not applicable in the future. In fact, emerging trends such as mobility-as-a-service, autonomous vehicles, and first/last-kilometer-solutions will revolutionize the future of transportation [121,122]. In contrast, model-driven approaches can provide the flexibility to plan with uncertainty, such as varying transport input parameters, and produce heterogeneous AS scenarios.

4. Modelling and Planning

Once the target is framed and the input data have been collected, the planners must develop a model. In most of the reviewed literature, CI problems usually involve the use of optimization algorithms to produce the AS, which is frequently complemented with a geospatial analysis. In this section, detailed discussions are presented on the methodologies through which the CI is allocated spatially and characterized in terms of electric attributes.

Whether a model or data-driven approach is taken (see Section 3.2), most of the literature investigates transport driving patterns and charging demand, but does not explicitly produce an output in terms of allocation and/or sizing of CSs, as pointed out by [116]. Categories of interest include:

- Public transit: in [123–125], the authors optimized charging-scheduling for public transit fleets. In [125], bus fleet charging operations are optimized in a way that includes the comprehensive effects of battery aging during night-time depot recharging.

In this case, municipalities and public authorities could benefit from optimization algorithms in order to assess the extent to which the implementation of electric vehicles can complement already existing public transport patterns.

- Smart charging: [110,126,127] explore how flexibility and V2G schemes can reduce peak load under grid constraints. The authors of [128] optimize scheduling through consideration of both V2G and G2V schemes, but without including a power flow analysis.

- **Controlled charging:** in [129], the authors investigate controlled charging strategies based on price sensitivity, where the PHEV users can decide whether to charge the vehicle, offering some benefits in terms of social acceptability and charging control penetration. The research concludes that few economic benefits can be derived out of V2G for PHEV users.

The quantification of flexibility and its effect on the grid is a highly investigated topic: the interest of these studies can support policies in favor of the active participation of EVs in the electric power system to increase renewable generation and decrease stress on the electrical infrastructure. Obviously, the quantification of the economic value of flexibility is of interest to investors, who aim to lower the total cost of ownership of recharging points through V2G energy market transactions [130].

4.1. Geospatial Analysis

A minor part of the reviewed literature considers geospatial analysis, wherein geographic data are manipulated through clustering methods or density calculations in order to map possible CI locations. In [37], candidate locations for CSs in urban areas are obtained from the superimposition of six geospatial data layers, including spatial data of the electric power distribution network, public transport stations, residential statistics, parking areas, etc. The geographical information is then partitioned into cells and buffer zones (effective areas for hosting CS around a point of interest), which can be used by urban planners to design future CI. The methodology enables the urban planners to rank the layers according to their importance. The authors of [3] use a hexagon overlay method to allocate CI, based on factors such as destination types, categories of residential areas, and distinguishing between night-time (potentially slow home charging) and day-time charging. Other factors include socio-economic parameters, such as average income, the presence of tourism, and geographical factors (e.g., presence of slopes). A more complex but similar approach is implemented in [66]: in this case, 15 criteria are used to allocate CSs in Ankara, Turkey. These criteria range from environmental factors (such as distance to vegetation, water, slope, and earthquake risk) to economic factors (land cost, EV ownership, and power cuts), as well as criteria concerning urbanity (proximity to main road, junction, petrol station). Once defined, these criteria are prioritized through a fuzzy analytical hierarchy process, as in [131]. The most important factors assessed are EV ownership, distance to power cut, and vegetation. Finally, the process ranks geographical locations by similarity to the ideal solution in terms of Euclidean distance. However, ref. [40] uses a graph analysis to extract reasonable links, which are a set of links that are feasible for site FCSs, and primary nodes. Through the calculation of a distance matrix and the quantification of the daily traffic flow on each link, CSs are finally allocated and sized. In [47], the authors develop an algorithm to locate and size charging stations for drayage trucks, both in the short-term and the long-term, using daily truck activities and geospatial analyses of truck yards locations within budget and grid constraints.

4.2. Optimization

4.2.1. Only Allocation

Although few articles optimize the number and size of chargers but do not allocate them spatially [51], a relatively large amount of studies among ones reviewed make use of transport data while solely solving the allocation problem. For example, the authors of [29] take into account the cost of investment for CSs through a multistage approach in which future costs are discounted to the present worth. New O–D pairs are sequentially added to the transportation network, and cities are successively chosen based on a statistical prediction of EV adopters (a logistic regression analysis is used). The added value of this study is in its effort to couple topological dynamics based on user adoption with economic benefits. The authors of [41] aim to allocate CSs for buses or logistics companies, but they allow chargers to have unlimited charging outlets. In contrast, they minimize costs by optimizing the charging operation schedule. However, ref. [39] models en-route charging

stations and in-depot charging stations, with the aim of substituting a certain number of conventional buses in the Salt Lake City area. Finally, the authors of [3] distribute a fixed amount of CSs throughout the territories of Hungary (budget constrained problem) without determining their charging power. It is important to analyze the charging outlets' number and power rating in order to assess the coincidence factor, the overall aggregated load for the electrical infrastructure, and, possibly, the flexibility resource.

4.2.2. Allocation and Sizing

This section explores articles implementing optimization algorithms: Tables 4–6 provide a visual overview of the literature assessment. Most of the authors use a strategy of cost minimization to produce the AS output, considering different cost parameters: the choice to include or neglect some of those parameters leads to prioritizing one stakeholder over the others. Following this logic, it is outlined as stakeholder oriented planning. In the context of AS, three different actors were observed to be relevant: charging service providers (entities that invest and operate CSs), DSOs, and final users. In the following sections, cost specifications are categorized depending on the single stakeholder they are attributed to: the more one article stresses one category of cost, the more the planning is going to be oriented towards that actor. It must be said that some authors deployed multi objective optimizations strategy to consider all the actors involved: an explicit example is [23] in which the authors developed “a proper trade-off between the contrasting interests of different stakeholders”.

4.2.3. Charging Service Provider Oriented Planning

- CS Investment Costs: present in most of the cases.
- Installation Costs: in [52], the authors vary whether the CS is located at an existing gas station. Installation is found to include raw material, an added line to connect CSs to the power grid, etc.
- Operation and Maintenance: this can also include staff salaries, as in [59,63,65,132].
- Land Costs: were recognized as being an important parameter in [51], especially in sizing and locating parking lots for EVs [27,28].
- Penalty Costs: the cost of applying demand response programs, as in [24].

The authors of [83] do not provide an AS strategy, but their algorithm can serve as an investment decision tool to avoid stranded assets and an oversized charging system (low average rate of use). However, insufficient infrastructure investments lead to poor voltage quality. The approach draws on a Monte Carlo simulation to estimate EV charging hosting capacity (defined as the number of simultaneous customers who can charge at a power outlet at any given time) for low voltage networks in Sweden.

4.2.4. Final User Oriented Planning

- User Costs: include purchasing electricity with TOU, added costs deviating from original patterns to reach the charging station [58,59,132], and parking costs [132].
- Penalty Costs: these costs can be useful for quantifying the cost of applying demand response programs, as in [24], and quantifying range anxiety caused by trip unfeasibility, as in [30].
- Overall Downtime: this generally consists of charging, traveling, and waiting time. It is used in multi-objective optimizations [23,52] or as the only decision variable, as in [48]. Study [56] calculates that solutions with higher quality of service (shorter waiting time) present significantly higher costs of the CI. Waiting time is counted as a cost in [21,43], calculated through the travel time cost extracted from a survey. In several studies, such as [82], downtime is calculated to assess the quality of the service (QoS) but is not included in the objective function.
- Charging Coverage: together with downtime, this is a critical parameter to ensure an optimal QoS of the CI and is a measure of user satisfaction [84]. In literature, the authors use different factors to quantify charging coverage, e.g., in [62], the factor is

the number of charging EVs; in [22], the factor is inversely proportional to the distance between two adjacent CSs on the same road; and [38,133,134] aim to maximize the flow captured in their model-driven study. The authors of [81] decide to minimize the overall number of charging locations without compromising the coverage of the trajectories in the mobility scenario. However, they do not take into account any costs in their optimization procedure.

4.2.5. DSO-Oriented Planning

- Grid Expansion Costs: these are evaluated in few articles: [84] includes substation expansions (power dependent) and feeder upgrades (length and power dependent).
- Energy Losses: many studies include losses in the electric network [25,32,53,58–61,63] due to charging-discharging behavior. This factor is usually counted as a cost through electricity price ([61]), but also as energy units, as in [55], which implemented a multi-objective optimization. In contrast, the authors of [65] make use of three indices to maximize the power quality, minimize active and reactive power losses, and finally impose a penalty on substantial voltage deviations. However, it should be noted that economic losses due to an added charging demand of EVs in the electric system do not translate into a significant change in the cost function.

Table 4. Planning: service provider oriented.

Ref	Year	Charging Station	Installation	O&M	Land	Penalty
[23]	2019	✓	✓			
[24]	2018	✓	✓			✓
[25]	2016	✓	✓	✓		
[28]	2016	✓	✓	✓	✓	
[29]	2016	✓	✓			
[30]	2018	✓	✓			✓
[32]	2019	✓	✓			
[34]	2019	✓	✓			
[39]	2018	✓	✓			
[41]	2016	✓	✓			
[42]	2017	✓	✓			
[43]	2017	✓	✓	✓	✓	
[44]	2018	✓	✓	✓		
[46]	2017	✓	✓			
[82]	2020	✓	✓		✓	✓
[50]	2017	✓	✓		✓	
[51]	2019	✓			✓	
[52]	2019	✓	✓			
[53]	2016	✓		✓		
[54]	2016	✓	✓	✓		
[56]	2019	✓	✓	✓		
[58]	2019	✓		✓		
[59]	2018	✓	✓	✓		
[60]	2017	✓			✓	
[61]	2019	✓		✓		
[63]	2014	✓		✓		
[65]	2017	✓	✓		✓	
[67]	2018	✓	✓			
[119]	2019	✓	✓	✓		
[132]	2020	✓	✓	✓		

O&M: operation and maintenance.

Table 5. Planning: final user oriented.

Ref	Year	U	P	CT WC	CC
[20]	2016				✓
[21]	2016			✓	
[22]	2019	✓			✓
[23]	2019			✓	✓
[24]	2018	✓	✓		
[28]	2016	✓			
[30]	2018		✓		
[38]	2017				✓
[41]	2016	✓			
[43]	2017	✓		✓	
[48]	2019			✓	
[81]	2020				✓
[82]	2020		✓		
[50]	2017	✓			
[51]	2019			✓	
[52]	2019				✓
[54]	2016				✓
[55]	2016				✓
[57]	2016			✓	
[58]	2019	✓			
[59]	2018	✓			
[60]	2017	✓			
[62]	2016	✓			✓
[63]	2014	✓			
[67]	2018	✓			
[119]	2019	✓		✓	
[132]	2020	✓		✓	✓

CT: charging time, WC: waiting cost, CC: charging coverage.

There is a body of literature that analyzes grid impacts from high-power charging on the distribution system but does not assess the monetary cost of it. In [135], the dynamic voltage stability of distribution grids is investigated using a modified version of the IEEE 13-bus system. Study [136] investigates the integration of high-power CI into low- and medium voltage grids, providing a detailed view of the electrical grid and challenges/possibilities related to the integration of high-power charging. This approach is applied to two electrical networks: a simple system composed of nine buses and a 69-node radial network. In [60], the authors are the first to include the hourly grid load to precisely estimate grid losses for the minimization of grid costs related to FCSs. In this case, an AC power flow is implemented in a network of 13 buses. The analysis in [59] focuses on added power losses through harmonic distortion injection in a 47-bus Malaysian radial distribution system. The authors conclude that significant power losses can occur without a proper harmonic pollution mitigation. The authors of [137] compare how different modes of transport can impact the grid, taking into account demand side management, such as ripple control. In the user case, a light rail transit is compared to the electric demand that would result from the electrification of a small portion of the urban ICEV fleet. The authors conclude that the impacts of the EV on the local grid could be insignificant if they are well managed through demand side management (DSM), whereas light rail transit would require upgrades to some substations. Instead, if no DSM strategy is applied, the power level required by the EV fleet is seven times higher than that required by the rail transit. The study provides an interesting perspective comparing two transportation systems, one public and one private, that are equivalent in terms of the passenger kilometers provided daily.

Table 6. Planning: DSO-oriented.

Ref	Year	Grid Expansion	Energy Loss	Electrical Network
[22]	2019	✓		✓
[23]	2019	✓		✓
[24]	2018		✓	✓
[25]	2016		✓	✓
[28]	2016		✓	✓
[32]	2019		✓	✓
[82]	2020		✓	✓
[50]	2017		✓	✓
[51]	2019	✓		
[84]	2020	✓		✓
[53]	2016		✓	✓
[55]	2016		✓	
[58]	2019		✓	
[60]	2017		✓	✓
[61]	2019		✓	✓
[62]	2016		✓	✓
[63]	2014		✓	
[65]	2017		✓	✓

It is worth noting the double optimization approach taken by authors in [42]: cost- and energy-based optimization. The second approach aims to minimize carbon emissions and prioritize energy conservation, even with the implementation of a larger capital investment. Whereas, in [57], an accurate simulation model is complemented with a genetic algorithm, which solves the problem of allocating FCSs, in order to minimize the added time for charging and costs. A similar hybrid resolution scheme is also applied in [32]. The two problems of AS are solved simultaneously in most of literature investigated. However, in [38], the problem of allocation and capacity design are decoupled and solved one after the other.

4.3. Distributed Energy Resources

In the reviewed literature, there is a growing effort to include distributed energy resource (DER) and storage systems as positively co-existing with EV charging stations. However, most of studies only include intermittent generation and batteries from an operational perspective: authors of [138] produce a charging strategy based on pricing for buses and taxis to maximize renewable generation use, whereas [139] concludes that V2G can support renewable energy production with a reduction in emissions and grid costs. In [140], the authors analyze how storage can improve V2V schemes for EV parking lots served by both slow and fast chargers, avoiding construction of new charging facilities. In [141], renewable generation is included in the operations optimization of an EV aggregator in parking lots. The authors of [84] conduct a noteworthy piece of research, wherein a cost-benefit analysis is conducted to assess whether ESS allocation can be beneficial to avoid grid expansion investments (substations and feeders) at charging substations. Chargers are located unmethodically at electrical bus nodes, which does not allow for any AS choice. Still, in the optimization, authors include comprehensive system upgrade costs, total costs of the ESS, day-ahead market prices, and operational benefits to apply arbitrage. Only a few articles contemplate how DERs can affect AS of CI. Study [119] implements wind and solar generators together with the use of lithium-ion batteries. In their cost-benefit analysis, the authors design a charging station coupled with DERs components to prioritize cost-effective solutions that consider electricity market patterns and grid limits. The authors find that investing in distributed energy resources (DERs) is profitable, although upfront costs increase up to four times compared to the baseline scenario (energy is bought 100%

from the grid). A particular feature of this research is that authors consider a very wide range of vehicles that can be charged at the station: bikes, small and large private cars, and vans. The authors of [61] consider both gas-based turbines and PV installations together with CSs, with the objective to minimize annualized social costs. For this purpose, the study comprehensively integrates emission costs, network losses, and EV battery degradation as well as optimal scheduling. The approach taken by [67] includes allocating and scheduling DERs, lead-acid batteries, and CSs. Results show that PV installations are allocated over battery devices due to large feed-in tariff, whereas optimal solutions can decrease grid expenses by almost 75% with consistent avoided energy losses.

Few articles analyze the coupling of controllable loads with charging stations in order to increase benefits for self-consumption and minimize grid impacts. Algorithms were developed in order to optimize operations and implement control strategies. This is the case in [142], where authors consider whether coupling thermal boilers' power demand with EVs can largely decrease the peak-to-valley difference if more EVs participate in the peak-shaving strategy. To the best knowledge of the authors, no AS study exists that takes controllable loads into account. This is probably due to the fact that controllable loads are regulated at the household level, and home-charging does not involve a planning process. Instead, the planning process is of more interest to public-charging stations at a municipal, regional, or national level.

Table 7 shows the resolution methods applied to solve AS problems. The most consistent procedure involved metaheuristic methods, with a strong presence of genetic algorithms such as non-dominated-sorting GA (NSGA-II). Deterministic approaches were categorized instead depending on the problem formulation used: optimization methods are usually solved in MATLAB or GAMS environments through common solvers such as GUROBI or CPLEX. In a few cases, the implementation of hybrid algorithms was observed, but only to solve the problem of scheduling. The authors of [27] use GA to allocate and size parking lots for EVs, whereas a second optimization is performed on schedule through linear programming to minimize user costs. Similarly, the authors of [67] use a genetic algorithm for the planning process, whereas the schedule is solved through non-linear optimization to minimize annual cost of energy.

Table 7. Optimization resolution methods.

Procedure	Methods/Formulation	Refs
Metaheuristic	PSO	[22,24,65]
	GA	[23,25,27–30,52,57,58,60,65,67]
	Binary Lightning	[59]
	Ant colony	[20,63]
Deterministic	MISOCP	[32,61]
	NLP	[67]
	MILP	[27,39,41–45,58]
	ILP	[46]
Accurate simulation		[38,51,57]
Discrete choice	Nested logit (Bayesian game)	[50]

5. Socio-Economic and Environmental Impacts

CI planning must follow the principles of sustainability to harmonize technological advancements with environmental concerns and overall societal benefits. This section briefly reviews the methodologies used to quantify impacts and results from the introduction of charging infrastructure that ultimately leads to EV adoption. According to a recent LCA investigation from Transport & Environment, the average EU car emits about three times less CO₂ than petrol and diesel cars [143]; emissions show a wide range of variability depending on the country where the car is charged. Results put in perspective the potential of emissions reduction through electrification of mobility, which will rapidly increase in the

short term due to renewable penetration upsurge. Moreover, the potential benefits of electrification could be further enhanced by technologies such as connected and autonomous vehicles, which are more feasible in the near future for freight and public transport.

As emphasised in the Introduction, technological advancements and infrastructure expansion are not the only nor the most effective pathways to achieve sustainable mobility: behavioural change incentives, transition to mobility-as-a-service [121], usage of public transport through first-kilometer/last-kilometer solutions, limitations of car traffic, and land use policies all have the potential to increment livability and socio-economic returns, especially in smart cities of the future. The impacts resulting from the implementation of these solutions vary depending on many characteristics, such as population density, household income, pollution, congestion levels, etc. However, assessment and application of technology-based solutions have been a large focus of the literature review, namely the electrification of private vehicles. Globally, the vast majority of road users have not yet adopted EVs, and it remains an early adopter phenomenon in most countries. One reason for this is that the user's propensity for purchasing EVs is hindered by range anxiety, which is the driver's concern of running out of battery power before they reach their destination [144] (source of larger concern for long-distance trips). This could be exacerbated by the fact that users are transitioning from ICEVs, which can ensure non-stop use in the range of 700 up to 1000 km. Contrary to expectations, infrastructure expansion (building new roads, bridges, etc.) is not the optimal solution for traffic congestion, and induced travel has been recognized as a limiting factor [145]. As reported by [146], a reduction in car accidents and congestion in urban and densely populated areas were assessed to represent the main share of benefits, whereas a reduction in pollution could be limited by added driving mileage. Instead, the electrification of public transport was assessed to be one of the most effective mitigation scenario in terms of CO₂-eq but not in terms of air quality (PM 2.5) [147–149]. In [150], the authors quantify the impacts on energy conservation and CO₂ emissions through the electrification of E-taxis, E-buses, electric sanitation trucks, and rental BEVs. Their results show that, even considering the significant increase in ownership of sanitation trucks and buses (8.8% and 47.4%), electrification results in a decrease of 10% emissions and 18.2% energy consumption. Even so, the authors encourage the implementation of car sharing as a means of limiting worsening traffic conditions.

6. Discussion and Future Research Scope

The literature in this paper focused on private passenger vehicles, which constitute the largest share of road vehicles. However, electrification of other modes of transport, such as short-distance ferries, or the electrification of ports operational activities, are topics that will be key in upcoming years. Overall, most of the articles implemented a plug-in solution, with a considerable percentage of fast chargers. The review showed a lack of usage of coinciding factors in sizing and allocating high-power charging station (HPCS): not accounting for this parameter can lead to an oversized infrastructure. Long-term planning of charging stations should anticipate mobility scenarios while estimating societal benefits that they produce. All in all, it is a recognized need to further investigate holistic and integrated approaches that include trade-offs between socio-economic and environmental benefits and power grid constraints. For example, a new stream of research could consider aggregated controllable loads of energy communities together with public and private charging stations to integrate and positively couple loads and intermittent renewable generation.

Authors have outlined the following investigation areas that can further complement and expand the research on HPCS infrastructure planning:

- Model-driven approaches are assessed to be preferred: the authors believe that further use of real data could produce more accurate results to help investors achieve a more optimal development of CI and enable regulators to produce policies that aim for sustainable mobility scenarios.
- There is a strong focus on the urban context for electrification. To the best knowledge of the authors, only one study produces an AS strategy for rural areas. More research

is needed in this field, especially due to the divergent conditions between rural and urban regions.

- Only a limited number of studies analyzed the electrification of highway networks. In particular, a profitability assessment of HPCS in large transport systems is missing, especially in terms of optimized number, location, and size [13].
- There is a lack of studies that investigate how to plan electrification for heavy duty vehicles (HDV)s. Although the European Parliament is setting short-term targets on new HDV fleets [151], there is not a solid scientific basis for the best practices to supply this mode of transport.
- Land: as in Section 4.2.3, it was highlighted as one of the most influential parameters for cost estimation of CI planning, but more analysis could be developed on the revenues generated by areas designated to EV charging compared to other final uses.
- Policies: the present review article did not include current and future trends in policies, barriers, and threats on charging infrastructure development and other factors that could enhance the uptake of EVs. For example, V2G and V2X regulation could decrease operational cost for grid operators and final users (especially when in combination with V2B applications), and we suggest future investigation on the scope.
- Future trends: more research must be developed to take into account trends such as ownership-to-service, shared vehicles, technological advancements of electrical scooters, and autonomous vehicles, etc. In this regard, autonomous vehicle technologies and shared mobility are predicted to complement each other in the future of transportation with positive feedback loops [73,121,152]. However, to the best knowledge of the authors, no studies have assessed AS coupling automotive EVs offering car-sharing services.

7. Conclusions

The review presented in this paper analyzes the state-of-the-art literature on CI planning. It categorizes studies and provides a clear overview of the important parameters that are necessary to both size and spatially locate charging stations for supplying EV fleets. The reviewed content has been organised in several categories to effectively describe how models can be formulated in their heterogeneous aspects. In fact, depending on the approach, the type of data available, and the type of vehicle the study focuses on, studies on CI planning can be formulated through different methodologies.

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