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Too much or not enough? Planning electric vehicle charging infrastructure: A review of modeling options

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ABSTRACT

While the transportation sector is responsible for a growing share of greenhouse gas emissions, electric vehicles (EVs) offer solutions for greener mobility. The proportion of electric vehicles in transportation fleets is increasing, but wider adoption will not be possible without an appropriate charging infrastructure. The deployment of such infrastructure should follow a strategy that considers both the environment in which it is deployed and the behavior patterns of electric vehicle users. If these aspects are not taken into consideration, there is a risk of failing to meet users' needs and generating additional costs. Here we review the literature on location problems for electric vehicle charging stations. We aim to draw up a comparative overview of approaches that have been used up to 2020 for optimizing the locations of charging infrastructure. We first briefly review the issues raised by the deployment of charging infrastructure, namely technical, economic and user acceptance concerns. We then look at the goals of the infrastructure location models in the literature. Schematically, those goals fall into two categories: minimizing the cost of charging infrastructure for a given level of service, or maximizing the service provided for a given cost. Finally, we focus on the approaches used to achieve these goals. Three categories of approaches are identified: node, path, and tour- or activity-based approaches. We then discuss these approaches in relation to technical, economic and user acceptance factors in order to provide a comprehensive analysis for stakeholders involved in EV charging infrastructure planning. Directions are given for future research to develop models that better reflect the real-world picture.

1. Introduction

The climate emergency requires a drastic and rapid reduction in anthropogenic greenhouse gas (GHG) emissions, which are the cause of the fastest global warming ever observed [1]. The transportation sector is responsible for about 15% of global GHG emissions (27% in the European Union), and this rate is expected to increase in the coming years [2]. A transition from internal combustion engine (ICE) vehicles to greener transportation could be a major lever for reducing global GHG emissions.

For road transportation and individual mobility, which account for the largest share of transportation-sector emissions, electric vehicles (EVs) emerge as a major alternative to ICE vehicles. Considering the whole lifetime of the vehicle, EVs have a lower global warming potential than ICE vehicles, especially if they are coupled with low-carbon electricity production systems [3]. Moreover, EVs have many other benefits, such as no tailpipe emissions – which could help avoid air pollution and exposure to nitrogen oxides, volatile organic compounds, and carbon monoxide in urban areas, and reduce particulate matter emissions – and far less noise than ICE vehicles.

Despite all these benefits, large-scale uptake of EVs is bottlenecked by a number of different barriers [4]. A first major barrier is the high purchase price of EVs compared to ICE vehicles, although the purchase price impact is expected to diminish shortly. When considering total cost of ownership over the whole life cycle, an EV is already less expensive than an ICE vehicle in countries such as Norway or France [5]. Moreover, the purchase price of EVs is projected to drop below that of ICE vehicles by 2025 [6]. The second main barrier for users is tied to range anxiety. Most EVs have a lower driving range than ICE vehicles. Even though the range offered by a full-charge battery is sufficient for daily use for a large majority of users, they fear that they will run out of battery before being able to finish their trips or find a charging point. User anxiety is thus the main problem to address to enable large-scale

Abbreviations: AC, Alternative Current; DC, Direct Current; EV, Electric Vehicle; EVSE, Electric Vehicle Supply Equipment; FCLM, Flow-Capturing Location Model; FRLM, Flow-Refueling Location Model; GHG, Greenhouse Gas; ICCT, International Council on Clean Transportation; ICE, Internal Combustion Engine; MCLM, Maximum Covering Location Model; PHEV, Plug-in Hybrid Electric Vehicle; SCLM, Set Covering Location Model

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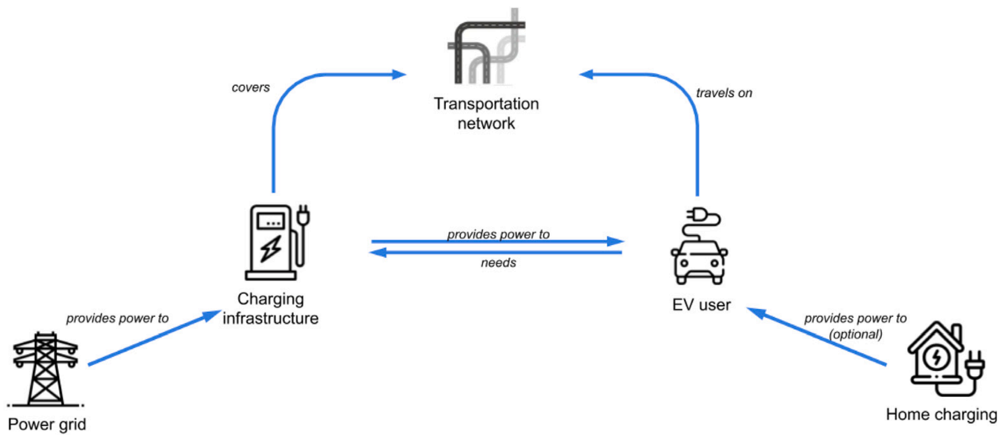

Fig. 1. Overview of the charging infrastructure framework.

EV adoption. The way forward could be to increase battery capacity to improve EV range or to provide an efficient charging infrastructure to better cover charging needs. However, even with a larger range, the fear of not being able to charge EVs when the battery is empty is still the same [7], so large-scale EV deployment cannot be achieved without a prior appropriate charging infrastructure [8]. Furthermore, research shows that investing in charging infrastructure is more efficient than subsidizing larger batteries as long as the investments in charging infrastructure are not sufficient to cover the whole territory [9–11].

However, deploying a charging infrastructure is hugely expensive and comes with several technical and economic constraints. The Energy Transition for Green Growth act in France sets a target of 7 million EV charging stations (public and private) by 2030, which corresponds to a minimum cost of around 2 billion euros [12] while an ICCT report projects an estimated 1 billion dollars in investment over the 2019–2025 period for the USA to fill its public charging infrastructure gap [13]. These huge costs warrant a proper deployment strategy to efficiently locate and scale new charging stations in order to favor large-scale EV adoption while avoiding resource waste or underinvestment for infrastructure investors. This deployment, with the costs it entails, also faces a chicken-and-egg problem: drivers will be reluctant to buy an EV without adequate infrastructure, while operators will refuse to invest in infrastructure until there is sufficient demand to make it profitable. To ease this bottleneck, the first step must be taken by operators [14].

Once the first step has been taken, the issue of optimal deployment of a vehicle refueling infrastructure is not a new challenge. Coverage and location models, such as those of Toregas [15] or Hodgson [16], have been around for a relatively long time and are perfectly applicable to gas refueling stations. However, EVs have different demands to ICE vehicles (charging takes longer than refueling), which makes these coverage models incompatible with routine EV use. Models taking these specificities into account have thus been developed since the end of the 2000s.

Nevertheless, few of them seem to take advantage of the benefits offered by electric vehicle charging, which does not require the user to be present during charging time. Moreover, the deployment of such an infrastructure does not happen all at once, partly because of the problem of the development costs it would generate without a guaranteed return on investment from a demand that will take a long time to come, which brings us back to the previous chicken-and-egg problem. An incremental and over-time deployment must be considered, considering the early stages of the infrastructure already present in the territory.

This literature review aims to provide an overview of the timely problem of EV charging infrastructure planning in terms of the optimization models used to determine optimal locations of charging points, and sizing. It explores and compares a rapidly growing scientific literature proposing strategies and simulation models for deployment of electric charging infrastructures, considering the technical, economic and user-side aspects of EVs.

To identify the first relevant articles, the Google Scholar database was searched with combination of keywords : {EV, electric vehicles, charging infrastructure, charging stations} and {planning, location, model, optimization}. We kept a sample of 287 articles containing literature reviews and papers on infrastructure optimization and deployment models cited as references in this field. The articles cited in these papers and the articles also citing them were then screened, and we added 63 relevant articles to our review.

The paper is structured as follows. Section 2 explains the different charging technologies and the issues involved in deploying charging infrastructure. Section 3 presents the objectives and targets of infrastructure deployment. Section 4 then covers the methods for locating and sizing infrastructure in a territory, and Section 5 highlights gaps in the literature and avenues for future research.

2. Background on charging infrastructure and the allied issues

The issue of deploying charging infrastructure for EVs is set in the following framework: EV users with limited autonomy travel the road network. Making these trips consumes energy, which in turn decreases the state of charge of the EV battery and creates a need to charge, which can be met in two ways: either through home/office charging, or through public (or semi-public) charging infrastructure. This infrastructure needs to stay at a reasonable cost for operators, who have limited investment capacity, while giving EV users the transportation network coverage they need. The goal is to enable drivers to use their EVs with less range anxiety, knowing that they can rely on public charging infrastructure when they need it. As public charging infrastructure supplies energy from the grid, infrastructure deployment needs to consider the constraints linked to power grid operation (see Fig. 1).

In this framework, three main types of issues are to consider when deploying charging infrastructure : technical, economic and user-centered issues.

2.1. Technical overview of charging devices

Charging devices provide the link between electricity grid and EVs by converting AC power into DC power, which can charge a battery. They can be on-board or off-board, depending on the type of charging.

The International Electrotechnical Commission (IEC) defines four charging modes [17]. In the first three modes, the EV is directly connected to the AC distribution network, and the conversion to DC is done through the vehicle's onboard charger. The main difference

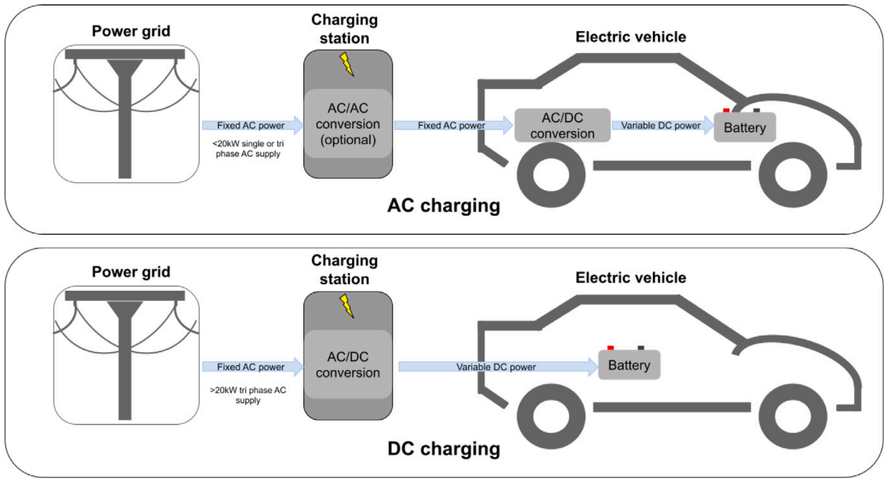

Fig. 2. Simplified architecture of EV charging.

between these three levels lies in the level of safety and charging control, which allow the vehicle battery to be charged with more or less power. For example, mode 1, which is used for low-power charging, is equivalent to plugging the vehicle into an electrical outlet, while mode 3 allows advanced charging control and higher charging power. The mode 4 is mostly used for fast charging applications. Unlike the three first modes, here the connection of EVs to the AC grid is not direct: the AC power is converted into DC power in an off-board charger, and then used to charge the EV's battery. Fig. 2 gives a simplified illustration of EV charging.

2.2. Charging infrastructure and EV acceptance

Charging EVs generally requires much more time than filling up an ICE vehicle gas tank. Charging times go from a few dozen minutes for the fastest chargers up to more than 20 h for the slow ones [18]. Charging stations thus have different design and management imperatives to conventional gas stations. EVs have different refueling behaviors due to different required charge-times and charging locations, especially when taking into account one of the major conveniences offered by EVs, i.e. that EV batteries can charge while the vehicle is not in use for mobility purposes (while parked at home, the workplace, in mall parking, etc.). Home EV charging does not require any effort from the driver other than plugging in the EV. It also does not require any specific installation – at least not for slow charging [17] – even if the majority of EV drivers install specific equipment to increase charging speed and for safety aspects. Moreover, in 90% of cases, trips do not exceed 80 km, whereas the typical range for an EV is about 200 km[1] [20,21]. Thus, home charging should be sufficient for a large majority of users: with a fully charged battery when leaving home, they could complete their daily trips and charge their EV once back home, ready for the next day.

However, home charging has some limits. First, if trips – or a succession of trips – exceed the EV range, then drivers need to be able to charge their EV elsewhere than at home. If this is not possible, then EVs will remain as a second car for the wealthiest percentiles of the population, since users will not be able to use it to make occasional long journeys and will therefore prefer an ICE vehicle [8]. Moreover, in many countries, a large part of the population do not have a single-family home with a private parking space where they can install a charging point [22]. This illustrates that relying solely on home charging for the transition from ICE vehicles to EVs will leave important barriers to the adoption of electric mobility, justifying the need for an appropriate public charging infrastructure.

The range and charging constraints of EVs make it illusory to envisage the broad diffusion of EVs without sufficient charging infrastructure. At the same time, if there are not enough EVs on the road, there will not be enough interest in setting up an expensive, unprofitable charging infrastructure. But without this infrastructure, it is illusory to envisage the democratization of EVs... The chicken-and-egg problem in this two-sided market has been studied by Delacretaz et al. [23] who show that an initial infrastructure has little immediate positive effect on EV adoption but that positive effect does increase over time. They also show a snowball effect: the demand elasticity for EVs relative to charging infrastructure provision increases with infrastructure development. In other words, the more charging stations there are, the greater the increase in EV demand with further investment in charging infrastructure.

This raises the question of marginal – or incremental – infrastructure development. An infrastructure is deployed in a spatial context, but also in a temporal one, and it is unrealistic to consider instantaneous deployment of a complete set [24]. It is therefore important to define a temporal deployment sequence along with a spatial set of locations to determine the most cost-effective investments [25]. Otherwise, the risk is to end up with an infrastructure unsuited to driver needs at the beginning, which would not allow the diffusion of EVs to start and thus discourage additional investments in infrastructure, and so on (again, a chicken-and-egg paradigm). In addition, even though charging stations are often deployed without a global vision, they nevertheless already exist in the territory, and it would be a mistake not to consider this existing resource. We must therefore think about the problem of placing 'one more charging station' and the value of this station when there is already a set of operational stations, while almost all the models focus on optimizing the final charging infrastructure without considering the process to get there.

2.3. Economical issues

A naive approach would be to consider the best option is to put fast chargers everywhere, as people value the option to charge quickly [26]. However, a DC fast charging station costs much more than a slower one. The average cost for a level 2 public charging station is $3000, while the average cost of a DC fast charging station is nine times more (Table 1).

[1] Note : This is valid for the European market, where the population densities are rather high and the distances to be traveled relatively small. In the case of the US or similar markets, the distances involved may be higher. However, they remain well below 200 km, which is already a pessimistic estimate of the range of a standard electric vehicle [19].

Table 1
Electric vehicle supply equipment (EVSE) purchase and installation costs in the U.S. [13].

EVSE type	Average public installation cost	Average home installation cost
Level 1	$4000	$400–$900
Level 2	$6000	$680–$4100
DC fast charging (50 kW)	$73,000	Not available
DC fast charging (150 kW)	$120,000	Not available
DC fast charging (350 kW)	$205,000	Not available

Since more expensive infrastructure should lead to more expensive charging service for users, a poor choice of electric vehicle supply equipment (EVSE) penalizes not just the consumer but also the operator for whom a charging station adapted to local needs guarantees a better return on investment. Let us explain this with a simple example. Suppose a charger able to fully charge an EV in three hours is placed in a site where parking times are usually eight hours. A person who leaves their EV parked and plugged in will charge for a maximum of three hours but then unnecessarily occupy the terminal for the remaining time. However, for the same budget, several slower charging stations could have been installed which would maximize the profit for the operator and the level of service for users.

Finally, it is important in the case of several operators that they coordinate with each other to ensure interoperability and good global coverage. But it is also important to put in place regulations to prevent the creation of local private monopolies in public parking areas, which would be harmful to users [27].

2.4. Power grid issues

Another issue in charging station location concerns the power grid. Level 1 infrastructure only requires about 3 kW from the power network, which is no more than common household appliances. This should not have a big impact on the wider grid, even when several EVs are simultaneously charging, or at least not one that a small tariff incentive could not solve. However, current fast chargers can require up to 150 kW from the grid, which is not necessarily scaled for that, especially if there are several fast chargers at the same place, as is the case with charging hubs. Placing chargers requiring too much power in non-adapted locations can stress the existing infrastructure and lead to the need for grid reinforcement, which can be very expensive [28].

The choice of charging station type and placement can therefore be a source of cost inefficiencies. To control the total cost of the infrastructure, this choice must be considered in relation to the real needs of users, as well as the capacity of the power grid.

Charging EVs is not simply a source of grid stress but also a potential source of grid stability if combined with smart grid management to exploit positive synergy with renewable energy production. Renewable energies are a source of stress for the electricity grid, as they are not or only partially controllable. Therefore, they sometimes produce too much energy with respect to the needs, and this surplus of energy has to be used. The batteries of EVs can then store this surplus energy produced by renewables to smooth out excess power output. Scheduling the charging of vehicles according to the constraints of the electrical grid is often called "smart charging".

EVs can also provide additional power to the grid during grid stress episodes by injecting electrical power from their battery into the grid, like a generator [29]. This bi-directional mechanism is commonly called Vehicle-to-Grid (V2G). Through this mechanism, EVs can notably flatten consumption peaks and play a role in regulating grid incidents by providing ancillary services to the grid, such as frequency regulation, resource adequacy, network deferral, energy arbitrage, spinning reserve, etc. [30] They can also directly fast-charge other vehicles, avoiding power demand peaks from fast charging on the distribution network [31].

2.5. Summary

In summary, the charging infrastructure for EVs needs to address technical issues linked to the technology used and the constraints it places on existing grid infrastructures. It also meets financial challenges: the costs related to charging infrastructure are relatively high, so it is important for operators to avoid making unnecessary investments and to be assured of a return on their investments. Finally, charging infrastructure needs to respond to user demand in order to garner user acceptance of EVs.

The financial stakes and public acceptance of EVs are closely linked: insufficient coverage of the territory, i.e. underinvestment or unwise investment, will discourage users from buying and using an EV. This in turn will have consequences on return on investment, as would prohibitively high utilization cost of the infrastructure. The technical constraints linked to the charging station energy supply can lead to significant additional costs linked to the electrical network. Finally, the adoption of EVs requires a charging infrastructure technology that meets users' expectations. Users expect to have at their disposal an infrastructure that suits their needs in a convenient way, and that they can rely on.

3. Overview and scope of planning simulation models

An appropriate EV charging infrastructure has to satisfy technical, economic and acceptability constraints. The infrastructure must address a threefold issue: its location, i.e. its distribution on the transport network, its capacity, i.e. the demand it can serve, and its users. In addition, infrastructure deployment can serve different goals depending on the interests of those deploying it on the transportation network.

To describe a transportation network in a location problem, we decompose it into nodes and paths (or links). The simplest strategy is to define one in relation to the other: a path or route is a link between two nodes, and a node is the intersection point of two paths, or can be the end of a path too.

Users make trips in the transportation network, i.e. they travel between two nodes. They also make tours, i.e. series of trips. During those trips, EV users use energy from their batteries, and sometimes need to charge their EVs with charging infrastructure in public space.

3.1. Users and charging infrastructure utilization

Location and sizing of the charging infrastructure must meet user demand. The literature mainly focuses on three types of charging-infrastructure users: buses, taxis, or private vehicles. A classification has been made in the table in Appendix.

Charging infrastructure is easier to design for buses, as buses have fixed tours with (more or less) precise time schedules, so uncertainties about their state of charge, availability or itinerary is quite low. For this problem, there are two options. If the buses have enough autonomy to run all day long without being charged, they can simply be charged at the end of their shift at charging stations installed at the depot. The second option is to place fast charging stations at bus stops to allow all buses to complete their tours, as described by Wang et al. [32]. The stops at charging points do not even have to be longer than at other bus stops, as current flash charging technology is able to charge two or three kWh into bus batteries in a couple of seconds. In this case, the choice could even be made to place a fast charging point at each bus stop, allowing the buses to be equipped with low-capacity batteries. These two options are not mutually exclusive, and it is possible to charge buses at night and add charging stations for buses that are unable to complete their tours.

For taxis, as fuel is a large part of their costs and they mainly make short trips, EVs could be an excellent option, and taxis could become a good showcase for the usefulness of EVs,[2] but the charging infrastructure has to meet specific requirements. First, electric taxis cannot charge during trips with a customer: they have to charge during idle time. However, these downtimes must be as short as possible. This is why it is critical here to consider the time spent at the charging station (waiting time and charging time), as it is idle time for the driver. Taxis already have many idle time situations, typically when waiting for customers. Charging time should not be an additional heavy constraint. Ideally, it should be available where and when taxis have idle time. Then, because it is common for taxi drivers to share a vehicle, home charging is not always an option: the charging infrastructure for taxis must allow them to operate continuously. The fast charging option is therefore often preferred for taxis.

Most of the literature focuses on private vehicles, which account for the biggest share of the vehicle fleet, or at least considers that an infrastructure can be developed for all light vehicles. Private vehicle owners have a wide variety of uses for their vehicles depending on their environment (rural, urban), travel habits (distance from their main points of interest, frequency of travel), and many other factors. The different ways of looking at the case of private vehicles are detailed in the rest of the paper.

3.2. Optimization goals

The literature has considered several optimization goals to effectively meet user charging demand.

Many studies aim to minimize the infrastructure costs for meeting a given demand, thus taking demand as a constraint. Like infrastructure costs, some papers only take the installation costs into account. These can be a simple fixed cost for any charging station, which can be actualized considering its life-cycle as in Dong et al. [33]. In this case, the objective narrows down to finding the configuration that allows to have as few stations as possible. The cost of charging infrastructure can also be made more complex if we consider the different costs of chargers and the construction costs, land costs as in Mehar et al. [34], or network reinforcement costs as in Rajabi-Ghahnavieh et al. [35]. Others take into account both investment and operation costs, such as maintenance costs or cost of electricity (Jia et al. [36]).

With a view to achieving profitability, several papers also aim to maximize the utilization of chargers (Cai et al. [37], Pevec et al. [38]).

Other studies choose to deal not with the infrastructure cost but with minimizing the user's costs. User costs are mainly tied to time spent waiting at charging stations (Hanabusa et al. [39], Tu et al. [40]), and the trip – or the deviation from their original path – they have to make to charge their vehicle (Ge et al. [41], Xu et al. [42]).

Some papers choose to focus on maximizing the number of EVs that could be charged at the station. In other words, the objective is to maximize EV flow at the charging station, based on the rationale that the more people have access to the infrastructure, the more useful it is. Some models only consider a location problem and provide a geographical coverage of the demand (Wang and Wang [43], Motoaki [44]). In this case, the objective is to have a maximum number of EVs with access to a potentially available station, and the charging station locations are uncorrelated to the charging station sizes. Other works consider the availability of the station, by introducing charging time during which the station is unavailable (Sun et al. [45]), or queuing models (Yang et al. [46]). This allows to address the question of sizing the infrastructure.

An alternative to maximizing EV flow is to maximize the amount of energy charged by the EVs (Chen et al. [47], Csizar et al. [48]) or the global distance they can travel (Wang et al. [49]), which is almost the same. This prevents many vehicles being covered by a single station, as can be the case with the previous objective. However, in this case charging 10 kWh in a single EV is the same as charging 1 kWh in ten vehicles, regardless of whether the intended trip is feasible for the vehicles. This is why some papers aim to build a charging infrastructure that minimizes failed – or maximize feasible – trips (Asamer et al. [50], Micari et al. [51]).

These optimization objectives are implemented using various location methods, as detailed in Section 4.

3.3. Sizing charging infrastructure

With the problem of location comes the problem of sizing the charging stations at the chosen locations. This is mainly a matter of answering two questions: how many charging points should be placed at a location, and which charging speed should be chosen. Locations are also dependent on station capacity, *i.e.* the number of vehicles that can be served within a certain period. For example, if a station with a large service capacity is installed at one location, there is limited interest in placing another station near it.

Some studies only focus on the problem of locating charging stations, sometimes considering an infinite capacity [43,52] which does not represent a real situation where charging points can only accommodate a limited number of vehicles. But once locations have been found without considering this limited capacity, charging stations can be sized according to the demand at each station, as in Micari et al. [51]. The sizing can be done simply with the number of EVs likely to need each station, or by more sophisticated models such as queuing models that can consider the randomness of charging demand, as in Zhu et al. [53]. However, not considering the capacity of charging stations in a first step of charging station location planning can lead to sub-optimal results, as the size of the stations influences their distribution over a territory.

Some models directly take into account limited capacity of their charging stations as a constraint, like the models proposed by Upchurch et al. [54] or Gavranovic et al. [55]. By doing so, it is possible to consider disparities in demand and avoid, for example, an area with a high concentration of demand being covered by only one station that will not be able to satisfy all the demand in its area. In addition, multiplying the number of stations in areas of high demand reduces the impact of a failure of one of them, which is important for the reliability of the infrastructure. Unlike the previous method, however, this approach leaves little flexibility in terms of the size of each station, since this parameter must be set beforehand.

Sizing the charging infrastructure is not just a matter of deciding the number of vehicles that can be accommodated, but also the time spent at the station. It is not always inconvenient that the charging process takes several hours, but this is not always acceptable, such as during long journeys requiring a quick charge to reach the destination. That is why it is also important to wisely choose the power level of charging stations based on the use case, and many models incorporate power sizing (You et al. [56], Wang et al. [57]). This sizing can also be done with each type of station chosen according to the type of targeted route, which allows fast charging stations to be placed where a quick charge is most useful. Indeed, even if increasing the charging speed of a station also increases its capacity as it serves EVs faster, slow charging stations are a more cost-effective option to meet the needs of a whole territory (Sun et al. [45]).

Finally, charging stations must be sized by considering grid capacity at the location of the charging points. As explained earlier, a large number of charging points at the same place or high power charging points cannot be installed where the electrical grid is too weak, at the risk of causing instabilities due to excessive power demand [58]. Some studies choose to take the characteristics of the electrical grid as a constraint (Zhu et al. [53], Zhang et al. [59]), and a few consider the

[2] Note: In Amsterdam Airport Schiphol, where there is the largest Tesla taxi fleet, taxis are massively using the free infrastructure provided by the car company, making it the most intensively used charging infrastructure in the world.

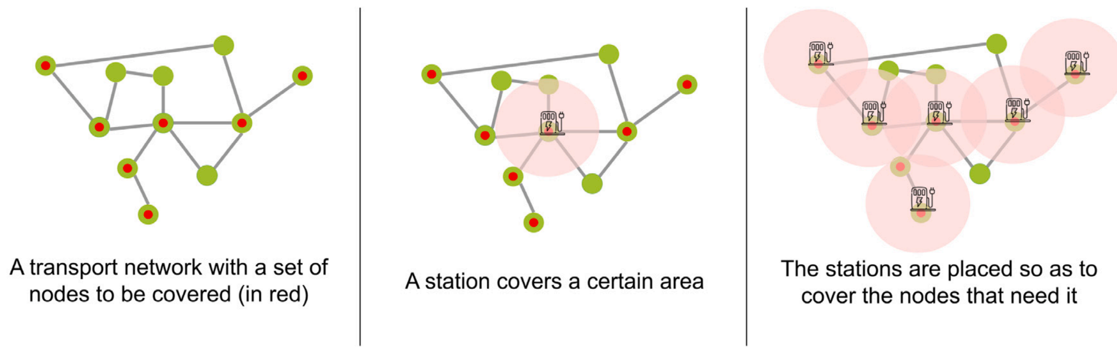

Fig. 3. Simplified principle of a node-based approach.

possibility of reinforcing the electrical grid (Sadeghi-Barzani et al. [60], Guo & Zhao [61]). Other grid-related issues, such as peaks in demand or power quality, may also arise because of charging infrastructure that does not take the power grid into account [62] or because of a power grid that does not take the charging infrastructure into account, depending on the point of view.

4. Location methods

Several methods to locate charging infrastructure have been developed, and most can be grouped into three main categories: node, path, or tour-based approaches [63].

The node-based approach is the most popular method for locating charging stations. It deals with the location problem as a facility location problem, which has been extensively studied for many applications [64]. The problem to be solved is formulated as follows. Given candidate locations which are the nodes, the objective is to place facilities, i.e. the charging stations, to meet the demand at the nodes. Even if it seems a simple formulation, this problem belongs to the NP-hard class, meaning that we are not able to find exact solutions in a reasonable time because the corresponding resolution algorithms have an execution time that increases exponentially in the problem dimension. Heuristic methods are often used to provide approximate solutions in a reasonable computing time. The principle of the method is illustrated in Fig. 3.

A second approach that has been considered is the path-based approach, introduced by Hodgson [16] and illustrated in Fig. 4. This approach relies on a flow-capturing model: the objective is to place charging stations along paths with the highest flows of vehicles, considering origin–destination trips, in order to serve as many users as possible. It considers effects that only emerge from the demand emanating from vehicle flows, whereas the node-based approach offers a relatively static view of demand.

Last, the tour-based approach, illustrated in Fig. 5, does not just consider individual origin–destination trips but the entire activity of an agent and its vehicle during a period. It considers origin, destination, distance traveled, vehicle paths and dwell times, to choose the best places to put charging infrastructures according to users' behavior.

4.1. Node-based approach

The Set Covering Location Model (SCLM) is a facility location model that aims to minimize the number of facilities while covering all the demand from the customers [15]. In this model, facilities are located in such a way that all demand points are not further from a plant than a certain determined distance. It assures all the consumers that they can find a facility under this distance, but does not consider the demand: all the demand points have the same weight, they just have to be covered. Wang and Lin [65] adapted this method and proposed a refueling-station-location model using a mixed integer programming method based on vehicle-routing logics with the aim of making all transportation network nodes accessible to each other. Later, Wang and Wang [43] used an SCLM to cover the maximum demand for both intra- and inter-city trips while minimizing cost, assuming that the capacity of each station is unlimited.

Another node-based approach is the Maximum Covering Location Model (MCLM) [66]. Its objective is to locate a given number of facilities to maximize coverage of the demand, considering a critical distance as the SCLM does: a facility covers a demand node if the distance from facility to node is under this critical distance. Unlike the SCLM, the MCLM allows some demand nodes to not be covered, so can be used when resources are insufficient to cover all the demand nodes, as is often the case in reality. However, both SCLM and MCLM consider the distance to determine if the demand node is geographically covered by the facility, without taking into account the impact of that distance: placing a plant at a demand node or at the node's critical distance is the same thing. Frade et al. [67] used the MCLM in a case study in Lisbon, Portugal to determine the locations of charging stations and then sized the stations according to the demand in each zone covered. Sun et al. [45] used a node-based maximum coverage model to locate slow charging stations in competition with fast charging stations placed with a flow-capturing model (see later). Wagner et al. [68] used a maximum coverage optimization and quantified the value of putting a charging station at points of interest such as schools or stores.

The p-median model first introduced by S. Hakimi [69] is now one of the most widely-used models in facility location problems. The objective of a p-median problem is to determine where to place p facilities among candidate locations to minimize the transportation cost (or weighted distance) between customers and facilities, with each customer assigned to a facility. The problem can be capacitated, meaning that the facilities have capacity restrictions on the amount of demand they can serve, and so the demand from customers assigned to this facility cannot exceed this capacity. In the case of charging stations, this means that only a limited number of cars can be served within a certain period, and therefore the availability of the station depends directly on its capacity. Gavranovic et al. [55] used this model on a subset of potential locations in Turkey, considering the demand and the preferences of local stakeholders. Jia et al. [70] separated the need for fast and slow charging, and used the p-median model to locate fast-charging stations. Jung et al. [71] also used the p-median in a bi-level problem to locate charging stations for taxis, while minimizing both distance to travel to the station and queue at the station. He et al. [72] estimated charging demand through socio-demographic data in Beijing and used this estimation as an input for all three node-based models (SCLM, MCLM and p-median). They found that the p-median model outperform SCLM and MCLM, and gives more stable solutions. An et al. [73] developed a two-stage optimization framework that considers the disruptions that could lead to charging demand changes.

Table 2 gives an overview of the node-based methods applied to EV charging stations location.

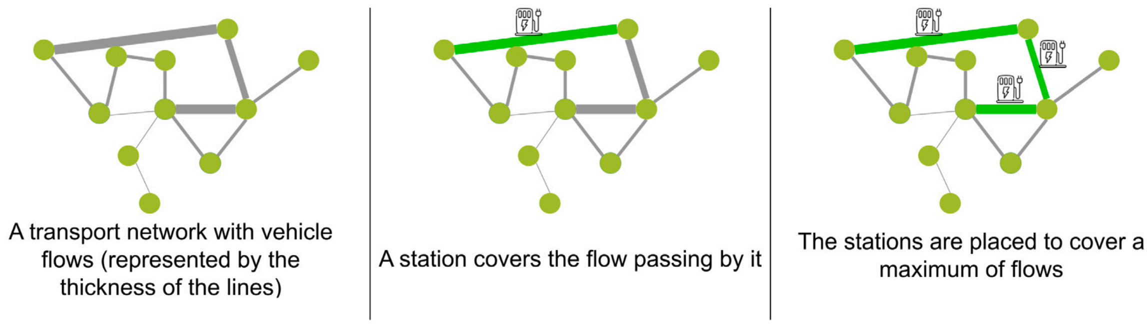

Fig. 4. Simplified principle of a path-based approach.

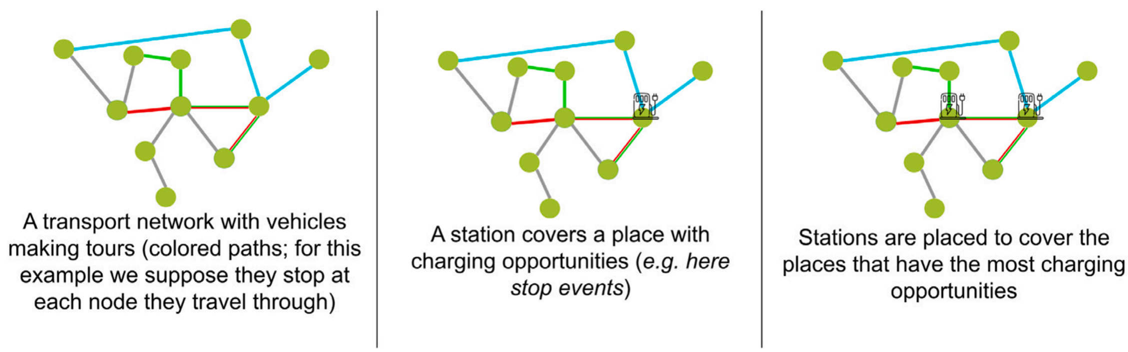

Fig. 5. Simplified principle of a tour-based approach.

4.2. Path-based approach

Instead of dealing with demand at nodes, Hodgson [16] introduced a path-based version of the MCLM called the Flow-Capturing Location Model (FCLM) with the hypothesis that traffic in a network can be served by several facilities located on common paths. The FCLM considers origin–destination pairs and aims to maximize the flow captured on the shortest path between origins and destinations. In this model, the path is considered covered if it passes through at least one node with a charging station.

The FCLM was later extended. Kuby and Lim [82] developed the Flow-Refueling Location Problem (FRLM) especially for alternative-fuel vehicles that considers the limited range of the vehicles, as a vehicle may have to stop at more than one refueling station in order to complete a path. They found that placing charging stations only at nodes would not be sufficient to provide total coverage, and then developed a method to locate stations on links [83]. Then, with Upchurch [54], they went on to develop the CFRLM, which is a FRLM with capacity constraints on the refueling stations. Wang et al. [57] used this model to place different kinds of stations, as previous models only take into account one type of charging stations. Kim and Kuby [84] then devised an optimization model that considers the deviations from the shortest path that drivers should have to make to refuel their vehicle, and Huang et al. [85] proposed a model with the possibility of multiple deviation paths. Li et al. [25] proposed a ‘multi-period multi-path’ FRLM with the objective to minimize the total cost of installations while making each trip feasible via at least one path between origin and destination within a reasonable tolerance compared to the shortest path, and considering the dynamics of the network over time. Further, Wu and Sioshansi [86] developed a stochastic FCLM model that takes into account the uncertainty of EV charging demand as soon as the infrastructure is built in anticipation of future EV adoption. Table 3 gives an overview of path-based methods.

4.3. Tour-based approach

The third method is the tour-based approach, sometimes also called activity-based. Jia et al. [36] proposed a model with the estimation of vehicle charging demand based on parking demand, measured in *vehicle-hours*. They assumed that the more occupied the parking slots are, the more charging demand there will be, regardless of turnover. Chen et al. [47] developed a parking-based model that considers the duration of parking time but excludes home parking. Cavadas et al. [92] also considered the possibility of demand transference between charging sites for users, meaning that the charging demand on distinct places can be transferred between those sites according to the users’ activities. You et al. [56] adopted a strategy based on missed trips in tours. Their optimization model tries to minimize the number of tours that could not be done due to a lack of charging stations. Andrews et al. [93] adopted a similar approach on missed trips but considering the available charging infrastructure. They developed a ‘user charging model’ that determines where and how EV users need to charge given the available charging methods. If a vehicle fails its trip due to a lack of infrastructure, it is taken as an input in an optimization program to place new charging stations. Cai et al. [37] proposed a data-driven method based on taxi data to put charging stations in existing gas stations. They extracted stop events to find charging opportunities at the different stations and estimated the potential charging demand for stop points in gas stations by evaluating state of charge according to previous tours. Shahraki et al. [94] used a similar method but focused on plug-in hybrid electric vehicles (PHEV). They looked at dwelling time between trips and estimated the state of charge of batteries after each trip, then placed charging stations to minimize the distance traveled by PHEV in combustion-engine mode. Gonzalez et al. [95] adopted a similar approach from simulation data, with an optimization concerning vehicles not able to complete their daily trips without modifying their initial behavior to charge their EV while considering electricity price fluctuations in order to minimize charging cost. He et al. [52] determined a bi-level tour-based model with traffic network equilibrium considering interactions between trips and charging needs

Table 2
Summary of articles using the node-based approach.

Method	Problem	Main optimization goal	Paper
MCLM	Location	Maximize the number of EVs charged	Frade et al. (2011) [67]
MCLM	Location	Maximize the number of EVs charged	Guo & Zhao (2015) [61]
MCLM	Location and sizing (capacity[a])	Maximize the number of EVs charged	Wang et al. (2013) [57]
MCLM	Location and sizing (capacity)	Maximize the number of EVs charged	Gopalakrishnan et al. (2016) [74]
MCLM	Location and sizing (power[b] and capacity)	Minimize the infrastructure cost for a given demand	Yang et al. (2017) [46]
MCLM	Location and sizing (power)	Maximize the amount of energy charged	Wagner et al. (2013) [68]
MCLM	Location and sizing (power)	Maximize the number of EVs charged	Liu, J. (2012) [75]
MCLM	Location and sizing (power)	Minimize the infrastructure cost for a given demand	Deb et al. (2019) [76]
p-median	Location	Minimize the distance (or deviation) to a charging station	Xu et al. (2013) [42]
p-median	Location	Minimize the distance (or deviation) to a charging station	Gavranović et al. (2014) [55]
p-median	Location	Minimize the infrastructure cost for a given demand	Jia et al. (2014) [70]
p-median	Location and sizing (capacity)	Minimize the distance (or deviation) to a charging station	Ge et al. (2011) [41]
p-median	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Mehar et al. (2013) [34]
p-median	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Sadeghi-Barzani et al. (2014) [60]
p-median	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Zhu et al. (2017) [53]
SCLM	Location	Maximize the number of EVs charged	Wang & Lin (2009) [65]
SCLM	Location	Maximize the number of EVs charged	Wang & Wang (2010) [43]
SCLM	Location and sizing (capacity)	Maximize the amount of energy charged	Csiszár et al. (2019) [48]
SCLM	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Andrenacci et al. (2016) [77]
SCLM	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Ghamami et al. (2016) [78]
SCLM	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Davidov & Pantoš (2017) [79]
SCLM	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Vazifeh et al. (2019) [80]
SCLM	Location and sizing (power)	Minimize the infrastructure cost for a given demand	Li et al (2011) [81]
Unclassified (node-based)	Location	Maximize charger utilization	Pevec et al. (2018) [38]
Unclassified (node-based)	Location	Minimize the infrastructure cost for a given demand	Rajabi-Ghahnavie & Sadeghi-Barzani (2017) [35]
Unclassified (node-based)	Location and sizing (capacity)	Maximize the number of EVs charged	He et al. (2016) [72]
Unclassified (node-based)	Location and sizing (power)	Maximize the distance traveled	Wang et al. (2019) [49]

[a]The sizing in capacity refers to number of EVs that can be served per unit of time.
[b]The sizing in power refers to charging speed (higher charging power means higher charging speed.

in the lower level and aiming to maximize social welfare in the upper level. Xi et al. [96] adopted a lower-resolution model, dividing a region into sub-regions for which the trip data between sub-regions is available. Their aim was to maximize the number of EVs that charge, or the amount of battery charged, with a trade-off between level 1 and 2 infrastructures under a budget constraint. They found that the efficiency of privileging level 1 or 2 infrastructure depends on the objective chosen, but that level 1 chargers are more cost-efficient if sufficient funds are unavailable.

An overview of the tour-based literature is given in Table 4. The tour-based methods are not really categorized, so the "Method" column does not appear contrary to the two previous tables.

Tour-based models often require a lot of data, which is often difficult to access for privacy reasons. Agent-based models – or multi agent models – can informatively simulate data and analyze traffic dynamics [49]. Chen et al. [101] used an agent-based model with autonomous EVs to place charging stations. This kind of model can be built from real travel data (travel surveys, etc.) and be used to compare users' behaviors among different charging infrastructure deployment strategies. Agent-based models can also be built to scenarios for study, which can be useful if there is insufficient data to validate a model principle. This can be valuable in the case of data-greedy tour-based models. Multi-agent models make it possible to track each agent in a studied population individually, and therefore carry out analyses in relation to the activities of that population, and provide explicit representations of tours [102]. Moreover, modeling tools like the MATSim project [103] have been developed to simulate populations' behavior with regard to the transport system, and they can be used to model energy demand [104].

4.4. Discussion

To sum up, Fig. 6 gives an overview of the methods previously discussed.

The main advantage of the node-based approach is that it needs little data, only requiring population density, which is relatively accessible. This makes the node-based approach an easy first estimate of charging station locations. However, there are limits to this type of coverage. For instance, the uncapacitated models only deal with coverage without considering the amount of demand. Second, this resolution pathway offers a static vision of the charging demand, which is not the case in reality: as previously stated, one of the main

Table 3
Summary of articles using the path-based approach.

Method	Problem	Main optimization goal	Paper
FCLM	Location	Maximize number of EVs charged	He et al. (2018) [87]
FCLM	Location	Maximize number of EVs charged	Motoaki, Y (2019) [44]
FCLM	Location	Maximize number of EVs charged	Riemann et al. (2015) [88]
FCLM	Location	Maximize number of EVs charged	Wu & Sioshansi (2017) [86]
FCLM	Location	Minimize the infrastructure cost for a given demand	Li et al (2016) [25]
FCLM	Location	Minimize waiting time at the station	Hanabusa & Horiguchi (2011) [39]
FCLM	Location and sizing (capacity)	Minimize failed trips (or maximize number of possible trips)	Micari et al. (2017) [51]
FCLM	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Dong et al. (2016) [33]
FCLM	Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Xiang et al. (2016) [89]
FRLM	Location	Maximize number of EVs charged	Kuby et al. (2005) [82]
FRLM	Location	Maximize number of EVs charged	Kuby et al. (2007) [83]
FRLM	Location	Minimize the infrastructure cost for a given demand	Huang et al. (2015) [85]
FRLM	Location	Minimize the infrastructure cost for a given demand	Li & Huang (2014) [11]
FRLM	Location and sizing (capacity)	Maximize number of EVs charged	Upchurch et al. (2009) [54]
FRLM	Location and sizing (capacity)	Maximize number of EVs charged	Zhang et al. (2018) [59]
Hybrid approach: node and path-based	Location	Minimize failed trips (or maximize number of possible trips)	Upchurch & Kuby (2010) [90]
Hybrid approach: path-based (fast charging) and node-based (slow charging)	Location	Minimize the infrastructure cost for a given demand	Huang et al. (2016) [91]
Hybrid approach: path-based (fast charging) and node-based (slow charging)	Location and sizing (power)	Maximize number of EVs charged	Sun et al. (2018) [45]

Table 4
Summary of articles using the tour-based approach.

Problem	Main optimization goal	Paper
Location	Maximize distance traveled	Shahraki et al. (2015) [94]
Location	Maximize number of EVs charged	He et al. (2015) [52]
Location	Minimize the distance (or deviation) to a charging station	Andrew et al. (2013) [93]
Location	Minimize failed trips (or maximize number of possible trips)	Asamer et al. (2016) [50]
Location	Minimize the infrastructure cost for a given demand	Wang et al. (2017) [32]
Location	Minimize waiting time at the station	Jung et al. (2014) [71]
Location	Minimize waiting time at the station	Tu et al. (2016) [40]
Location and sizing (capacity)	Maximize charger utilization	Cai et al. (2014) [37]
Location and sizing (capacity)	Maximize number of EVs charged	Cavadas et al. (2015) [92]
Location and sizing (capacity)	Minimize failed trips (or maximize the number of possible trips)	Dong et al. (2012) [97]
Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Han et al. (2016) [98]
Location and sizing (capacity)	Minimize the infrastructure cost for a given demand	Jia et al. (2012) [36]
Location and sizing (power and capacity)	Maximize the amount of energy charged	Chen et al. (2013) [47]
Location and sizing (power and capacity)	Maximize number of EVs charged or maximize the amount of energy charged	Xi et al. (2013) [99]
Location and sizing (power)	Minimize failed trips (or maximize number of possible trips)	You & Hsieh (2014) [56]
Location and sizing (power)	Minimize waiting time at the station	Kameda & Mukai (2011) [100]

advantages of a flow-based model over a nodal approach is that it can take into account issues that only emerge from the description of vehicle flows. Another issue is that node-based coverage can lead to a poor representation of charging needs. According to Hodgson [16], the demand in a network is not always expressed at nodes, as people generally will not make a trip from home to the charging station just to charge their vehicle. Furthermore, a node-based approach fails to deal with issues emerging from traffic flows such as cannibalization, meaning that charging stations cut into each other's coverage areas. In addition, Upchurch et al. [90] found that the flow-based method is more stable as the number of charging stations to place increases, which is really important when planning over time. That is why many studies explicitly integrate the effect of flows into the location of charging stations [25].

However, this flow-based approach is not suitable for all cases. Flow-based methods consider that EV charging will be done quickly before continuing the trip to the primary destination, just as any ICE vehicle user would do. While this solution is possible with fast charging stations, which can refuel an EV in a dozen minutes, it is not possible for slow charging stations where EV batteries can take several hours to charge. Thus, the flow-based approach is not a substitute for the node-based approach, but complementary to it, depending on objective, territory, type of charging stations, etc. However, many studies only use one or the other category. Sun et al. [45] used a mixed-method approach, with location of fast charging stations for vehicle interception and a node-based approach to place slow charging stations in places where a long charging time is acceptable. However, flow-capturing models often fail to capture the uncertainty of EV charging demand, which can lead to less robust locations [86].

Given the issues with the flow-based approach, the tour-based approach is based not only on user driving patterns but more generally on user behaviors. This type of approach is sometimes also referred to as 'activity-based'. By considering events around the details of the sequence of trips, it allows a better representation of drivers' charging needs than the two previous approaches. By using real and individual data, the tour-based approach captures the randomness in the behavior of users, and allows to serve all users, which cannot be done with aggregated data, as illustrated in Fig. 7. In this case, both green and

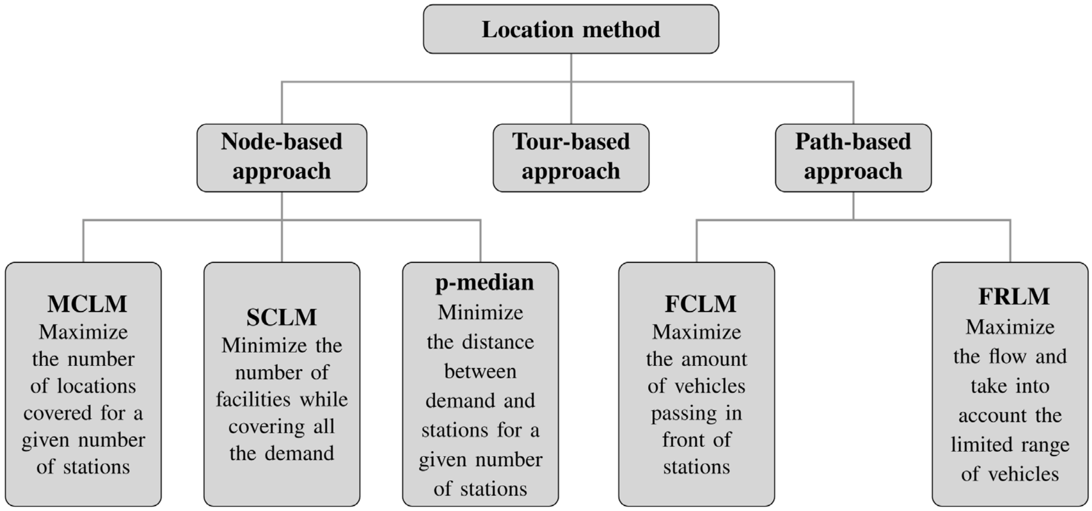

Fig. 6. Overview of location methods.

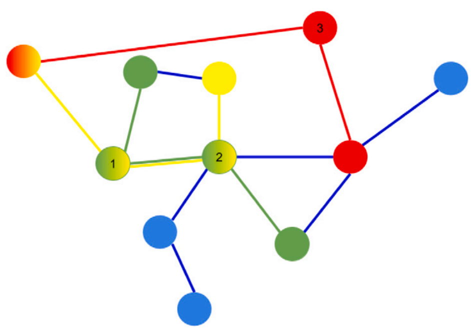

Fig. 7. Example of three paths.

Table 5
Main points of comparison between location methods.

Criteria	Method		
	Node-based	Path-based	Tour-based
Urban territory	+	−−	++
Highways	−	++	+
Representation of charging needs	−/+	+	++
User behavior	−	−/+	++
Data requirements	Very low	Low	Very high

yellow paths pass through nodes 1 and 2, and the red path passes through node 3. If two stations were placed based on aggregated data, they would be at nodes 1 and 2 that have the most traffic passing through, but the green and yellow vehicles would be served twice and the red one would not be served at all, which could have been avoided if using individual data.

However, as noted in most of the tour-based works, this method is often data-driven, with real or at least simulated data. It requires a large amount of highly detailed data, drilling down to at least the detail of individual trips and stops for a sufficiently large sample size to make the model realistic. This data can be hard to obtain. The mains points of comparison between approaches are summarized in Table 5

To conclude this section, note that many studies have been conducted for the purpose of planning the best possible charging infrastructure. They have been carried out with different criteria to be optimized according to the desired objective. However, while it is easy to check whether chosen criteria have been optimized, it is harder to measure the impact of this model on the population, in other words whether the criteria chosen are the right ones. The high cost of the infrastructure makes large-scale testing unfeasible. To overcome this problem, multi-agent models can help, as explained above. However, these models may be subject to simulation bias, and may therefore give an erroneous view of user behavior.

5. Conclusion

This paper analyzed models for deploying charging infrastructure and discussed the allied technical, economic, and user behavior-related issues.

The wide diffusion of EVs is a step towards greener mobility, which is one of today's big challenges. This transition from ICE vehicles to EVs cannot take place without infrastructure that greatly reduces early users' range anxiety and reassures potential future users that EVs are capable of providing the same services as ICE vehicles. For the time being, infrastructures have been developed with a limited real coherent overarching strategy. However, the underlying costs of necessary infrastructure to meet the needs of a large number of EV users, as well as the physical limitations of the electricity grid, make it imperative to coordinate and optimize the large-scale deployment of an electric charging infrastructure, failing which there is a risk of wasting valuable resources and of ending up with an infrastructure that is not adapted to user needs.

The scholarship has used several approaches for optimizing the deployment of charging infrastructure. These approaches can be collapsed into three categories: node-based, path-based, and tour-based. Although not specific to EV charging infrastructure planning, these approaches can readily adapt to consider the specificities of EVs instead of copying the gas station model, and facilitate the transition from ICE vehicles to EVs easier by minimizing the constraints of using EVs.

The node-based approach is easy to implement and suitable for certain areas such as residential neighborhoods, but it fails to capture the problems arising from vehicle flows. The path-based approach can address this gap, but it is better suited for highway use-cases and has the downside of leading to time-consuming infrastructure, which may prove a barrier for users to make the transition from ICE vehicles to EVs. The tour-based approach requires a lot of data and is therefore more difficult to implement, but it is able to consider user activities in order to get the best-adapted and least-restrictive infrastructure possible for users. With data on the activities of users, points of interest can be exploited to provide charging solutions at locations where there is demand, without users having to change their behavior [105].

The methods adopt different response strategies, regardless of the approach used. Some focus on maximizing served demand for a fixed

Table A.1

Paper	Approach	Problem	Limited resources	Charging type	Main optimization goal	Use case	Target environment	Home charging available	Electric grid aspect	Previous existing infrastructure
Wang & Lin (2013) [57]	Mixed approach	Location and sizing (power and capacity)	Yes (constraint)	Mixed	Minimize failed trips (or maximize the number of possible trips)	Private vehicle	Mixed environment	Unspecified	No	No
Upchurch & Kuby (2010) [90]	Node and path-based	Location	Yes (constraint)	Unique	Minimize failed trips (or maximize the number of possible trips)	Private vehicle	Highway	Unspecified	No	No
He et al. (2016) [72]	Node-based	Location and sizing (capacity)	Yes (constraint)	Mixed	Maximize the number of EVs charged	Private vehicle	Urban environment	Yes, not for all	No	No
Rajabi-Ghahnavieh & Sadeghi-Barzani (2017) [35]	Node-based	Location	No (budget to optimize)	Fast charging	Minimize the infrastructure cost for a given demand	Private vehicle	Urban environment	Yes, for all	Yes, as a parameter	No
Pevec et al. (2018) [38]	Node-based	Location	Yes (constraint)	Unique	Maximize the charger's utilization	Private vehicle	Mixed environment	Yes, not for all	No	Yes
Wang et al. (2019) [49]	Node-based	Location and sizing (power)	Yes (constraint)	Mixed	Maximize the distance traveled	Taxis and private vehicles	Urban environment	Yes, not for all	No	No
Frade et al. (2011) [67]	Node-based (MCLM)	Location	Yes (constraint)	Slow charging	Maximize the number of EVs charged	Private vehicle	Urban environment	Yes, not for all	No	No
Liu, J. (2012) [75]	Node-based (MCLM)	Location and sizing (power)	Yes (constraint)	Mixed	Maximize the number of EVs charged	Private vehicle	Urban environment	Yes, not for all	Yes, as a constraint	No
Wagner et al. (2013) [68]	Node-based (MCLM)	Location and sizing (power)	Yes (constraint)	Mixed	Maximize the amount of energy charged	Private vehicle	Semi-urban environment	Unspecified	No	No
Wang et al. (2013) [57]	Node-based (MCLM)	Location and sizing (capacity)	Yes (constraint)	Mixed	Maximize the number of EVs charged	Private vehicle	Unspecified	Unspecified	Yes, as a constraint	No
Guo & Zhao (2015) [61]	Node-based (MCLM)	Location	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Urban environment	Unspecified	Yes, as a parameter	No
Gopalakrishnan et al. (2016) [74]	Node-based (MCLM)	Location and sizing (capacity)	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Unspecified	Unspecified	No	No
Yang et al. (2017) [46]	Node-based (MCLM)	Location and sizing (power and capacity)	Yes (constraint)	Unique	Minimize the infrastructure cost for a given demand	Taxi fleet	Semi-urban environment	Unspecified	No	Yes
Deb et al. (2019) [76]	Node-based (MCLM)	Location and sizing (power)	No (budget to optimize)	Mixed	Minimize the infrastructure cost for a given demand	Private vehicle	Urban environment	Unspecified	Yes, as a parameter	No
Ge et al. (2011) [41]	Node-based (p-median)	Location and sizing (capacity)	Yes (constraint)	Unique	Minimize the distance (or the deviation) to a charging station	Private vehicle	Mixed environment	Unspecified	No	No
Xu et al. (2013) [42]	Node-based (p-median)	Location	Yes (constraint)	Unique	Minimize the distance (or the deviation) to a charging station	Private vehicle	Urban environment	Unspecified	No	No
Mehar et al. (2013) [34]	Node-based (p-median)	Location and sizing (capacity)	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Unspecified	Yes, as a constraint	Yes
Gavranović et al. (2014) [55]	Node-based (p-median)	Location	Yes (constraint)	Unique	Minimize the distance (or the deviation) to a charging station	Private vehicle	Mixed environment	Unspecified	No	No

(*continued on next page*)

Table A.1 (*continued*).

Paper	Approach	Problem	Limited resources	Charging type	Main optimization goal	Use case	Target environment	Home charging available	Electric grid aspect	Previous existing infrastructure
Jia et al. (2014) [70]	Node-based (p-median)	Location	No (budget to optimize)	Fast charging	Minimize the infrastructure cost for a given demand	Private vehicle with home charging	Semi-urban environment	Yes, for all	No	No
Sadeghi-barzani et al. (2014) [60]	Node-based (p-median)	Location and sizing (capacity)	No (budget to optimize)	Fast charging	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Unspecified	Yes, as a parameter	No
Zhu et al. (2017) [53]	Node-based (p-median)	Location and sizing (capacity)	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Unspecified	Yes, as a parameter	No
Wang & Lin (2009) [65]	Node-based (SCLM)	Location	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Unspecified	Unspecified	No	No
Wang & Wang (2010) [43]	Node-based (SCLM)	Location	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Unspecified	Unspecified	No	No
Li et al. (2011) [81]	Node-based (SCLM)	Location and sizing (power)	No (budget to optimize)	Mixed	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Unspecified	No	No
Andrenacci et al. (2016) [77]	Node-based (SCLM)	Location and sizing (capacity)	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Semi-urban environment	Yes, for all	No	No
Ghamami et al. (2016) [78]	Node-based (SCLM)	Location and sizing (capacity)	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Urban environment	No	No	No
Davidov & Pantoš (2017) [79]	Node-based (SCLM)	Location and sizing (capacity)	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Unspecified	No	No
Csiszár et al. (2019) [48]	Node-based (SCLM)	Location and sizing (capacity)	Yes (constraint)	Unique	Maximize the amount of energy charged	Private vehicle	Unspecified	Yes, not for all	No	No
Vazifeh et al. (2019) [80]	Node-based (SCLM)	Location and sizing (capacity)	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Semi-urban environment	Yes, for all	No	No
Huang et al. (2016) [91]	Path-based (fast charging) and node-based (slow charging)	Location	No (budget to optimize)	Mixed	Minimize the infrastructure cost for a given demand	Private vehicle	Semi-urban environment	Unspecified	No	No
Sun et al. (2018) [45]	Path-based (fast charging) and node-based (slow charging)	Location and sizing (power)	Yes (constraint)	Mixed	Maximize the number of EVs charged	Private vehicle	Mixed environment	Yes, for all	No	No
Hanabusa & Horiguchi (2011) [39]	Path-based (FCLM)	Location	Yes (constraint)	Unique	Minimize the waiting time at the station	Private vehicle	Unspecified	Unspecified	Yes, as a constraint	No
Riemann et al. (2015) [88]	Path-based (FCLM)	Location	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Mixed environment	Yes, for all	No	No
Dong et al. (2016) [33]	Path-based (FCLM)	Location and sizing (capacity)	No (budget to optimize)	Fast charging	Minimize the infrastructure cost for a given demand	Private vehicle	Highway	Unspecified	No	No
Li et al. (2016) [25]	Path-based (FCLM)	Location	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Mixed environment	Yes, for all	No	Yes

(continued on next page)

Table A.1 (*continued*).

Paper	Approach	Problem	Limited resources	Charging type	Main optimization goal	Use case	Target environment	Home charging available	Electric grid aspect	Previous existing infrastructure
Xiang et al. (2016) [89]	Path-based (FCLM)	Location and sizing (capacity)	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Unspecified	Yes, as a constraint	No
Wu & Sioshansi (2017) [86]	Path-based (FCLM)	Location	Yes (constraint)	Fast charging	Maximize the number of EVs charged	Private vehicle	Mixed environment	Yes, for all	No	No
Micari et al. (2017) [51]	Path-based (FCLM)	Location and sizing (capacity)	Yes (constraint)	Unique	Minimize failed trips (or maximize the number of possible trips)	Private vehicle	Highway	Unspecified	No	No
He et al. (2018) [87]	Path-based (FCLM)	Location	Yes (constraint)	Fast charging	Maximize the number of EVs charged	Private vehicle	Unspecified	Yes, for all	No	No
Motoaki, Y. (2019) [44]	Path-based (FCLM)	Location	Yes (constraint)	Fast charging	Maximize the number of EVs charged	Private vehicle	Unspecified	Yes, for all	Yes, as a constraint	Yes
Kuby et al. (2005) [82]	Path-based (FRLM)	Location	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Unspecified	Unspecified	No	No
Kuby et al. (2007) [83]	Path-based (FRLM)	Location	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Unspecified	Unspecified	No	No
Upchurch et al. (2009) [54]	Path-based (FRLM)	Location and sizing (capacity)	Yes (constraint)	Unique	Maximize the number of EVs charged	Private vehicle	Unspecified	Unspecified	No	No
Li & Huang (2014) [11]	Path-based (FRLM)	Location	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Yes, for all	No	No
Huang et al. (2015) [85]	Path-based (FRLM)	Location	No (budget to optimize)	Unique	Minimize the infrastructure cost for a given demand	Private vehicle	Unspecified	Unspecified	No	No
Zhang et al. (2018) [59]	Path-based (FRLM)	Location and sizing (capacity)	Yes (constraint)	Fast charging	Maximize the number of EVs charged	Private vehicle	Mixed environment	Yes, for all	Yes, as a constraint	No
Kameda & Mukai (2011) [100]	Tour-based	Location and sizing (power)	Yes (constraint)	Fast charging	Minimize the waiting time at the station	Bus or public transport	Urban environment	No	No	No
Dong et al. (2012) [97]	Tour-based	Location and sizing (capacity)	Yes (constraint)	Mixed	Minimize failed trips (or maximize the number of possible trips)	Private vehicle	Semi-urban environment	Yes, for all	No	No
Jia et al. (2012) [36]	Tour-based	Location and sizing (capacity)	No (budget to optimize)	Fast charging	Minimize the infrastructure cost for a given demand	Private vehicle	Urban environment	Unspecified	No	No
Chen et al. (2013) [47]	Tour-based	Location and sizing (power and capacity)	Yes (constraint)	Mixed	Maximize the amount of energy charged	Private vehicle	Unspecified	Yes, not for all	No	No
Xi et al. (2013) [99]	Tour-based	Location and sizing (power and capacity)	Yes (constraint)	Mixed (medium and slow charging)	Maximize the number of EVs charged or maximize the amount of energy charged	Private vehicle	Mixed environment	Yes, for all	No	No
Andrew et al. (2013) [93]	Tour-based	Location	Yes (constraint)	Medium charging	Minimize the distance (or the deviation) to a charging station	Private vehicle	Semi-urban environment	Yes, for all	No	No
Cai et al. (2014) [37]	Tour-based	Location and sizing (capacity)	Yes (constraint)	Fast charging	Maximize the charger's utilization	Taxi fleet	Semi-urban environment	Yes, for all	No	No

(*continued on next page*)

Table A.1 (*continued*).

Paper	Approach	Problem	Limited resources	Charging type	Main optimization goal	Use case	Target environment	Home charging available	Electric grid aspect	Previous existing infrastructure
You & Hsieh (2014) [56]	Tour-based	Location and sizing (power)	Yes (constraint)	Mixed	Minimize failed trips (or maximize the number of possible trips)	Private vehicle	Unspecified	Unspecified	No	No
Jung et al. (2014) [71]	Tour-based	Location	Yes (constraint)	Fast charging	Minimize the waiting time at the station	Taxi fleet	Urban environment	Unspecified	No	No
Shahraki et al. (2015) [94]	Tour-based	Location	Yes (constraint)	Unique	Maximize the distance traveled	Taxi fleet	Semi-urban environment	Yes, for all	No	No
Cavadas et al. (2015) [92]	Tour-based	Location and sizing (capacity)	Yes (constraint)	Slow charging	Maximize the number of EVs charged	Private vehicle	Urban environment	Yes, not for all	No	No
He et al. (2015) [52]	Tour-based	Location	Yes (constraint)	Medium charging	Maximize the number of EVs charged	Private vehicle	Unspecified	Yes, for all	No	No
Asamer et al. (2016) [50]	Tour-based	Location	Yes (constraint)	Mixed (medium and fast charging)	Minimize failed trips (or maximize the number of possible trips)	Taxi fleet	Urban environment	No	No	No
Han et al. (2016) [98]	Tour-based	Location and sizing (capacity)	No (budget to optimize)	Fast charging	Minimize the infrastructure cost for a given demand	Taxi fleet	Semi-urban environment	Yes, for all	No	No
Tu et al. (2016) [40]	Tour-based	Location	Yes (constraint)	Fast charging	Minimize the waiting time at the station	Taxi fleet	Semi-urban environment	Unspecified	No	No
Wang et al. (2017) [32]	Tour-based	Location	No (budget to optimize)	Fast charging	Minimize the infrastructure cost for a given demand	Bus or public transport	Urban environment	Unspecified	No	No

budget, which can be expressed in terms of the number of vehicles to be charged, volume of energy to be charged, time saved or number of feasible trips. Others consider charging demand as the primal condition and try to minimize the budget needed to satisfy it. While early work focused on the geographical placement of charging stations to meet charging demand, more recent models now also integrate the service capacity of the stations, introducing station sizing into the results. Charging speed used is rarely considered: many models consider only one type of charging station, thus defining only the number (and not quality) of charging points needed.

Few of the models other than node and parking-based models look to take advantage of the benefits offered by EV charging, which does not require the user to be present during charging time. This key advantage should be considered in order to plan a charging infrastructure that matches charging opportunities, to make EV use as unrestrictive as possible and thus encourage EV diffusion.

To conclude, the optimization models reviewed do not consider any temporality in deployment: for a given budget, the infrastructure is optimized as if all the stations were placed simultaneously. However, this kind an infrastructure does not get deployed all in one go, partly because of the development costs it would generate without a guaranteed return on investment from a demand that will take a long time to come. Charging infrastructure deployment will take place over a period that may last several years, and this factor should now be explored in order to have an infrastructure that provides acceptable coverage from the very beginning of its deployment, and not just once the last charging points have been installed. An incremental ‘over-time’ deployment must therefore be considered, factoring in the early-stage infrastructure already present in the territory, which very few models do (see Appendix), and the action of ‘adding one more station’.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Literature table

See Table A.1.

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