

# Electric vehicle charging infrastructure planning for integrated transportation and power distribution networks: A review



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## ABSTRACT

Environmental concerns and urban air pollution are major drivers for the transition from combustion engines to electric vehicles. To support a large-scale adoption of electric vehicles an efficient charging infrastructure roll-out is required. However, the optimal planning of charging stations is a non-trivial task, as it requires coordination between planning activities in the transportation and the power distribution network. Historically, the modeling of these two networks has been approached from different research areas and with the use of different methodologies. As a result, few papers embrace the combined problem to its full extent and the literature is highly scattered and represents different model perspectives and the targeting of many different objectives. In the paper, we present a systematic review of the literature that considers the combined investigation of transportation and distribution networks, with a focus on objectives, methodology and scope. It allows us to describe the current state of the art, to highlight research gaps and to propose directions for future work of the research community. The identified research gaps include, but are not limited to: 1) a general lack of integrated modeling approaches, 2) the need for increasingly detailed modeling of charging demand that accounts for randomness and variability in space and time rather than averages to support power grid planning, 3) the need to consider a mix of different types of charging options rather than only fast charging and 4) the need to shift from standard test networks and theoretical based planning approaches to large-scale and real-world case studies.

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## 1. Introduction

Global warming, caused by the extensive emission of greenhouse gases, is a major challenge of the 21st century. In 2017, the transportation sector accounted for 27% of the total greenhouse gas emissions in the European Union, of which passenger vehicles were responsible for about 44%. Transportation emissions have increased by more than 25% since 1990 and are expected to rise further without preventive policies [1]. There are many ways to pursue greenhouse gas emission reductions in the transportation sector and mitigate climate impacts, such as by promoting active travel, public transportation and electric mobility. While promotion of active travel and public transportation may prove to be an efficient measure for achieving greenhouse gas emission reductions under certain conditions [2], the overall impacts of such promotions are uncertain as they depend on the ability to change passenger

behavior and to substitute between transportation modes. Hence, the transition to electric mobility represents one of the most promising means to reduce greenhouse gas emissions in the transportation sector and to help alleviate urban air pollution. However, notwithstanding the environmental benefits of such transition, the phasing-in of electric vehicles (EVs) has been happening at a slow pace. This can be attributed to several factors, including high purchase costs, technological limitations such as the limited driving range, and uncertainty and concerns with respect to the capacity of the charging infrastructure (CI) [3,4]. The limited driving range combined with a lack of public CI results in the so-called range anxiety and is found to be an essential barrier for the large-scale adoption of EVs [5].

In lack of a generally accepted definition of different charging options, we distinguish between private and public charging. Private charging is hereby defined as home charging on private property. Public charging is used in its broadest sense to refer to both semi-public and public charging. This includes workplace charging, curbside charging and charging activities that take place at car parks or in relation to out-of-home leisure activities.

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## Nomenclature

|     |  |
|-----|--|
| CI  | Charging Infrastructure                  |
| DN  | Distribution Network                     |
| DSO | Distribution System Operator             |
| EA  | Evolutionary Algorithm                   |
| EV  | Electric Vehicle                         |
| FCI | Fast Charging Infrastructure             |
| NIO | Nature-Inspired Optimization             |
| P/C | Physics and Chemistry based Optimization |
| PV  | Photovoltaic                             |
| SoC | State of Charge                          |
| SI  | Swarm Intelligence based Optimization    |
| TN  | Transportation Network                   |

### 1.1. The importance of public charging infrastructure

The availability of private CI influences the readiness to buy an EV [6]. The importance of being able to charge privately is evident from the analysis of data collected during the early stages of EV adoption. More than 50% of EV owners rely solely on home charging [7–10]. However, future demand for public CI is expected to diverge significantly from the patterns observed in the early studies for mainly two reasons. First, without access to home charging, EV owners are exclusively dependent on public CI. The availability of having a permanent parking space at home and thus the possibility of home charging is dependent on socio-geographical characteristics, as supported by recent studies in Germany and the United States [11,12]. While the average home charging availability for rural areas is estimated to be around 80% in both countries, a significantly lower availability is expected for metropolitan regions. In Germany, the availability is estimated to be 67%, while for American homes it is only 60%. As a result, it is a requirement that the public CI especially for urban areas is further developed. Second, the public CI must be able to simultaneously support different types of demand of which many are expected to increase in the future. This includes demand from local users, taxis, city logistics as well as demand from long-distance drivers who visit the city. In summary, it is expected that the public CI will need a substantial expansion in the future to stimulate the increasing number of EVs as targeted by politicians and urban planners. While public CI plays a key role in the promotion of EVs, the planning of such CI is a non-trivial task. A critical factor when measuring the efficiency of a public CI is the utilization rate of the chargers [11,13]. Several international studies suggest that the utilization rates for the existing CI are low. In the Netherlands, it ranges from 4% to 5% [14,15], while in the United States and China slightly higher rates of 7% [16] and less than 15% [17] respectively have been observed. While individual EV users benefit from low utilization rates, low usage is often inefficient from a system perspective, highlighting the need for proper planning [18,19].

### 1.2. Previous review works on charging infrastructure planning

The problem of the optimal placement and sizing of public CI has received increasing attention in the literature over the past few years. Several review papers [20–31] have tried to classify the different approaches. In Table 1, we provide an overview of the content in each of these studies.

Articles [20,21] review the CI planning literature in terms of the optimization methodology and distinguish between approaches focusing on economic costs or grid impacts. While paper [21]

focuses on rapid charging, the review work in [20] does not restrict the review to a certain charging technology. Paper [22] provides a comprehensive overview of different spatial localization methodologies for the CI planning problem. The literature is classified in terms of three content levels. The first category deals with user, route or destination-oriented approaches while the second distinguishes between theoretical and empirical-based literature. The third is a classification of different result categories, namely demand density, partitioning and network optimization. The reviews in [24,28] focus on transportation network (TN) modeling approaches and corresponding placement methodologies. The work [26] provides a detailed review of nature-inspired optimization (NIO) algorithms applied to the CI planning problem. Another detailed review addresses the CI planning literature with a focus on wireless and conductive charging [29]. Study [30] provides a comprehensive review on the optimal location of CI with emphasis on objective functions, placement methodologies, geographic conditions and demand-side management. In [23,25] the review is structured according to the perspective of the different papers. That is, 1) CI planning considering exclusively the TN perspective; 2) CI planning considering only the power distribution network (DN) perspective and 3) CI planning where both perspectives are included. However, both reviews mainly concentrate on the first two categories. CI planning for integrated TNs and DNs is only shortly addressed in the works. On the contrary, the work in [27] solely focuses on the interdependence between the TN and DN. The review focuses on the equilibrium modeling of the TN and DN and highlights different applications. However, only a limited part of the review addresses the CI planning problem. Paper [31] presents another detailed review on EV CI planning with a focus on the modeling options, such as the demand modeling approach, objectives, charging type, use case or target environment. Even though the paper acknowledges the importance to include the DN perspective for CI planning, the majority of reviewed literature does not consider this perspective.

### 1.3. The importance of an integrated planning approach

While the planning of CI so far is mainly driven by the perspective of the TN, with the aim of overcoming range anxiety and increasing user convenience to accelerate the EV market ramp-up, there is an additional need to represent the DN perspective. This is due to the fact, that the development of CI has significant impacts on both road traffic and electricity consumption patterns. With respect to road traffic, the deployment of EV chargers will attract additional traffic to specific areas and increase search times for parking and charging in urban areas. In addition, increased EV traffic will introduce a different power consumption pattern and potentially, because it varies in time and over the geography, increase the risk of supply bottlenecks in the power system. The additional stress on the power grid from increasing shares of EVs can emerge in different forms, such as overloading of transformers [32–34] and power lines [34,35], increased system losses [36,37], voltage deviations [36,38,39], and phase unbalances [34,40,41].

Hence, a key challenge in planning future CI is to find an optimal geographical placement and sizing for new charging stations in a way that satisfies the transportation demand and at the same time is cost-effective from the power grid perspective. Taking into account both perspectives will not only reduce overall costs from a systems perspective, and thus increase social welfare, but will also accelerate the deployment of CI. New CI development is a lengthy process where the CI operator needs to contact the relevant distribution system operator (DSO) to apply for connecting the new CI at a targeted location. The inclusion of the DN perspective in the initial phase of CI planning can help identify alternative CI locations

**Table 1**

Content of existing review works addressing the planning of electric vehicle charging infrastructure.

| Ref. | Year | Demand modeling | Optimization methodology | Objectives | Constraints | Other CI planning related content  | Other review content                  |
|------|------|-----------------|--------------------------|------------|-------------|------------------------------------|---------------------------------------|
| [20] | 2015 | —               | x                        | —          | —           | —                                  | —                                     |
| [21] | 2016 | —               | x                        | —          | —           | —                                  | Charging technology & grid impact     |
| [22] | 2018 | x               | —                        | x          | —           | Case study                         | —                                     |
| [23] | 2018 | x               | x                        | x          | x           | —                                  | CI development in different countries |
| [24] | 2019 | x               | x                        | x          | —           | —                                  | —                                     |
| [25] | 2019 | x               | x                        | —          | —           | —                                  | Grid impact & benefits                |
| [26] | 2019 | —               | x                        | x          | —           | —                                  | —                                     |
| [27] | 2019 | x               | x                        | —          | —           | DN modeling & applications         | —                                     |
| [28] | 2020 | x               | x                        | —          | —           | Vehicle type                       | —                                     |
| [29] | 2020 | x               | x                        | —          | —           | Case study & techn. readiness      | Wireless charging projects            |
| [30] | 2020 | x               | x                        | x          | x           | —                                  | CI development in India               |
| [31] | 2022 | x               | —                        | x          | x           | Charging type, use case, DN aspect | —                                     |

that avoid bottlenecks in the DN and thus speed up the installation. It can also assist DSOs to prepare for the additional loading in the grid and be a means to reduce the stress on the power grid by analyzing the implications of different CI roll-out strategies and by considering smart charging strategies.

#### 1.4. Contributions

Following the analysis of existing review papers, to the best of the authors' knowledge, there is no comprehensive review of the CI planning literature that considers both the TN and DN perspective. Therefore, in comparison to the existing reviews illustrated in Table 1, we solely focus on literature that addresses the CI planning problem from a joint perspective by considering the problem from a TN and DN perspective. The main contributions of the paper consist of:

- 1) A comprehensive research-based survey of papers that consider placement and sizing of CI from a joint TN and DN perspective,
- 2) A classification of planning objectives based on the reviewed literature,
- 3) The analysis of demand modeling aspects and overall optimization methodologies,
- 4) The presentation and classification of studies with respect to charging technology, target area as well as the scale of case study and
- 5) The identification of a series of research gaps in the literature and the pinpointing of future research directions.

The subsequent parts of this paper are organized as follows. Section 2 provides a general overview of the CI planning framework for integrated TNs and DNs. Section 3 introduces a detailed classification of CI planning objectives based on the reviewed literature. Section 4 addresses the demand modeling approach of the reviewed literature, while Section 5 highlights the application focus in terms of charging technology, target area and scope of case study. Section 6 provides a summary and discussion of the main findings of the literature review, which is used to provide directions for future research in Section 7. Finally, conclusions are offered in Section 8.

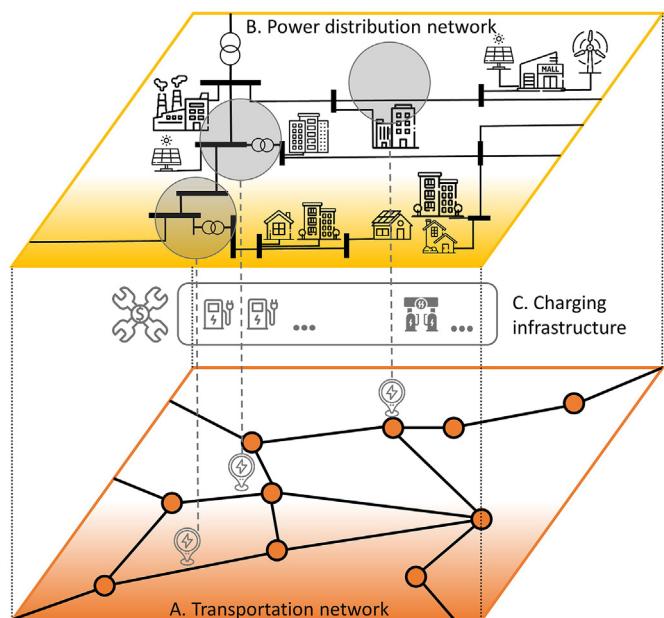
## 2. General overview of the charging infrastructure planning problem

CI planning for integrated TNs and DNs is concerned with finding the optimal location and capacity of charging stations in the TN conditional on the DN as illustrated in Fig. 1. Such problem is complex and non-trivial as it involves the interaction between the

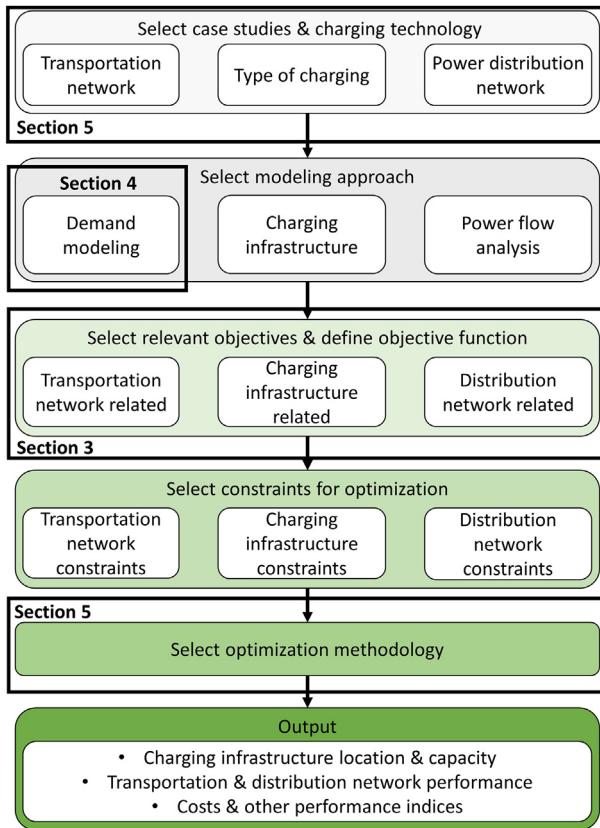
TN and DN, linked by the CI. Further to this, the decision on location and capacity of the CI may benefit one network while harming the other. While the location and capacity of CI will influence the quality of supply, travel behavior and charging convenience within the TN, it will affect the impact on DN and its related cost. Moreover, it will also influence the CI related costs.

A simplified flow-chart of the CI planning framework is provided in Fig. 2 covering six steps. Each step involves the three perspectives as illustrated in Fig. 1, namely the TN, DN and CI perspective.

The first step typically involves defining the application focus, which is further discussed in Section 5. The application focus includes decisions regarding the type of CI under study, the target area and the scope of the case study for the TN and DN, which is mainly determined by data availability. The type of CI concerns the charging technology to be deployed and is an important aspect as it influences charging speed and thus user convenience, while at the same time influencing the potential grid impacts and costs of the CI. DC fast chargers are significantly more expensive than AC slow



**Fig. 1.** Simplified illustration of the charging infrastructure planning problem for integrated transportation and power distribution networks. As illustrated, the transportation and distribution network are inherently linked by the charging infrastructure. While the bottom layer illustrates an exemplary transportation network, the upper layer represents an illustrative power distribution network.



**Fig. 2.** Simplified illustration of the charging infrastructure planning framework for integrated transportation and power distribution networks. The flow chart illustrates a typical sequence of decisions and actions required to solve the problem.

chargers [42] and may also cause more stress to the DN [43]. Hence, considering only one type of charging may lead to a non-optimal solution compared to a situation where a mix of different charging technologies is considered. The reviewed literature addresses both CI planning for solely slow or fast charging as well as CI planning for a mix of charging technologies. In this paper, charging with a capacity up to 22 kW is classified as slow charging while charging above this capacity is considered as fast charging. Studies that consider a mixture of at least two different charging technologies such as slow charging, fast charging or battery swapping are categorized as mixed charging. The target area refers to the area of CI deployment, such as urban, suburban and rural areas or highways, and is another important factor to decide on as it influences both the TN and DN structure as well as the EV user behavior. As an example, rural areas with a high share of home charging are potentially very different from urban areas where more cars rely on public charging. Last, the scope of the case study might determine the applicability to real-world problems. In this work, we differentiate the literature according to the data origin of the TN and DN. We distinguish between case studies solely based on test networks originating from literature for both the TN and DN as (T), case studies where at least one of the networks applies a real topology based on original data as (M) and case studies where both the TN and DN are based on original data from a real-life use case as (R).

The demand modeling approach for the TN involves the choice of CI location method, such as the node-based, flow-based and agent-based approach found in the reviewed literature, and choice regarding the use of queuing systems. Data availability plays a crucial part in the selection of the location method to be further

discussed in Section 4. Concerning the DN modeling, different power flow analysis approaches can be selected depending on the type of DN and its underlying conditions. It involves the choice of power flow mode (balanced AC, unbalanced AC or DC), choice of algorithm (e.g. Newton-Raphson, fast-decoupled or backward/forward sweep) and choice of the voltage level to be analyzed (e.g low voltage DN or medium voltage DN). The modeling approach of both the TN and DN will determine the detail and speed of modeling and hence exerts a major influence with respect to the scalability of the methods to large systems.

Once the study focus and modeling approach are defined, planning objectives and constraints for the CI optimization need to be selected. The selection of relevant planning objectives plays a crucial role in the outcome and applicability of the approach for real-life planning. Typically, the objectives can be categorized as being TN related, DN related and CI related to be further discussed in Section 3. Objectives should be carefully evaluated and selected, as different objectives usually lead to trade-offs between different perspectives, and therefore only the most important objectives, which differ according to the focus of the study, should be considered. Moreover, the constraints need to ensure a feasible solution of the optimization according to practical constraints. The constraints can be categorized as so-called equality constraints or inequality constraints. Equality constraints include the power balance for the DN and the charging demand balance for the TN. On the contrary, voltage and current limits of the DN, budget limits of the CI or travel time limits and limitations with respect to the number of charging stations within the TN can be modeled as inequality constraints. Again, the constraints are highly dependent on the study focus.

Finally, a suitable optimization algorithm needs to be selected dependent on the formulated objective function and constraints. The objective function can either be framed as a multi-objective problem with contradictory objectives or a single-objective problem with TN and DN related constraints. Popular optimization methods include conventional optimization approaches (such as linear, non-linear, integer, mixed-integer programming), NIO methods (such as genetic algorithm, particle swarm optimization or evolutionary algorithm) or hybrid approaches. While the former are optimization techniques for a system of linear or non-linear constraints and objective function where all or some of the variables are restricted by integers, NIO approaches mimic a natural phenomenon while hybrid approaches combine different methods with the aim of achieving superior results. The reviewed literature is classified according to the optimization methodology in Section 5. However, a comparison of the different methods is out of the scope of this paper and we kindly refer the reader to articles [26,44] for a more detailed discussion on the different optimization algorithms.

Typical outputs of the optimization are the optimized location of the CI and the capacity at each location under the given conditions. Furthermore, the TN and DN performance can be evaluated and overall costs of the CI deployment are determined.

### 3. Charging infrastructure planning objectives

As outlined in the previous section, the selection of CI planning objectives plays a crucial role in the planning results, which is why the reviewed literature should be analyzed by the objectives the research seeks to cover. By applying this perspective, information regarding the diversity, scope and trade-offs between the different objectives can be attained. The value of this perspective from a future research view is the ability to understand the range of currently supported objectives and how frequently they appear in the literature. This in turn is important as a means to identify

research gaps but also to link objectives with the modeling context. The reviewed objectives can be assigned to one of the three different perspectives illustrated in Fig. 1 and are thus classified as TN, DN and CI related objectives, depicted in Fig. 3.

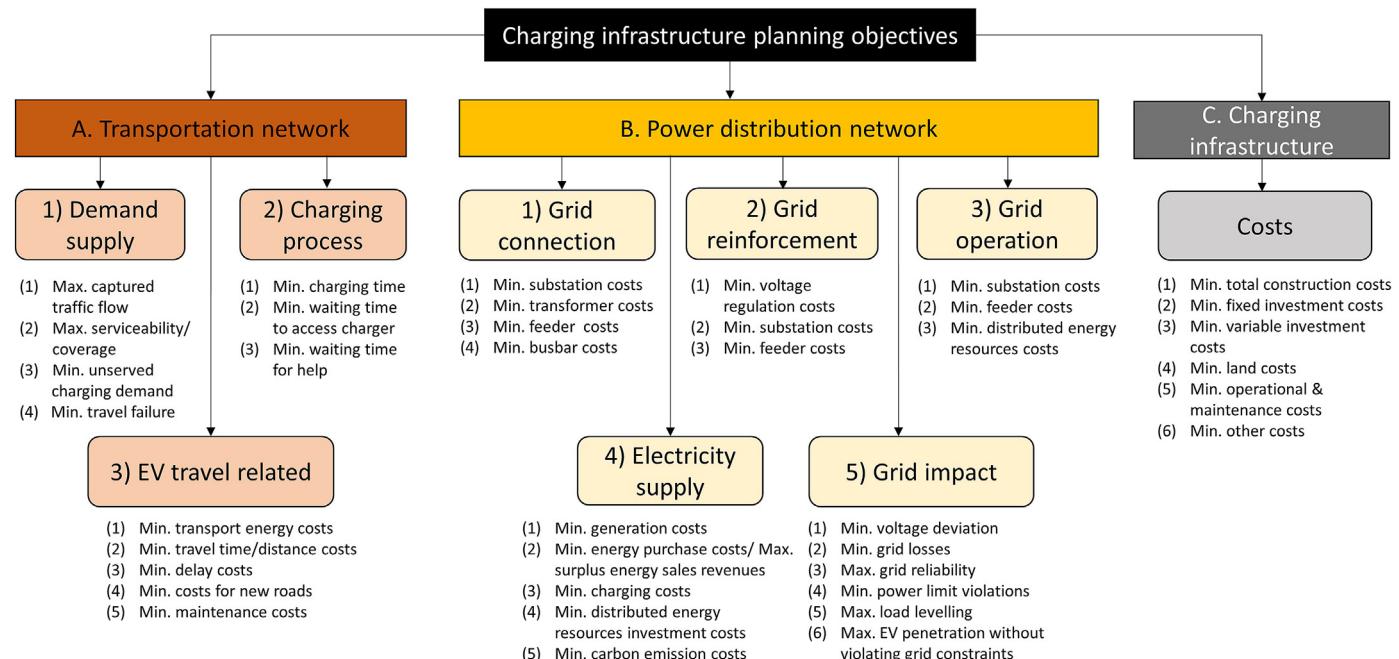
Table 2 provides an overview of the research objectives based on the classification presented in Fig. 3. There are two different types of studies. First, the majority of articles include both TN and DN related objectives. Second, studies [45–48] address either the TN or DN in the corresponding objective function and consider other network related effects as part of the constraints. While [45,46] use TN related objectives with DN constraints, [47–49] focus on DN related objectives and employ several TN related constraints, such as charging availability, service rates or maximum waiting times. In [50,51] the aim is to minimize CI related costs with respect to TN and DN constraints. In the following, the different objectives are discussed in more detail.

### 3.1. Transportation network related objectives

The TN related objectives cover all objectives that aim to optimize the CI within the TN with the goal of:

- 1) fulfilling the EV charging demand,
- 2) optimizing the charging process itself by considering relevant key performance indicators associated with the charging situation, or
- 3) more widely improving the conditions for EV drivers associated with the resulting travel patterns.

Ideally, an optimal CI is the result of serving several key performance indicators, which might include proximity to chargers and waiting time minimization. The first is important for slow charging, while the latter is important for fast charging. The three sub-categories of objectives are discussed in more detail below. In the following, we use bracketed numbers to refer to the objectives of each sub-category of objectives as illustrated in Fig. 3.



**Fig. 3.** Classification of electric vehicle charging infrastructure planning objectives used in the reviewed literature. The three different perspectives, namely transportation network related, distribution network related and charging infrastructure related, are indicated with the respective color as used in Fig. 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

**Table 2**

Overview of the combinations of charging infrastructure planning objectives based on the classification presented in Fig. 3

| Year | Ref. | A. Transportation network |                     |              | B. Distribution network |                       |                   |                       | C. Charging infrastructure |
|------|------|---------------------------|---------------------|--------------|-------------------------|-----------------------|-------------------|-----------------------|----------------------------|
|      |      | 1) Demand supply          | 2) Charging process | 3) EV travel | 1) Grid connection      | 2) Grid reinforcement | 3) Grid operation | 4) Electricity supply |                            |
| 2013 | [52] | (1)                       |                     |              |                         |                       |                   |                       | (1), (2)                   |
| 2013 | [86] |                           |                     | (2)          |                         |                       |                   | (1), (3)              | (1)                        |
| 2014 | [53] | (1)                       |                     |              | (1), (2), (3)           | (2)                   |                   |                       | (2)                        |
| 2014 | [81] |                           |                     | (1)          | (3)                     |                       |                   |                       | (2), (4)                   |
| 2016 | [46] | (2)                       |                     |              |                         |                       |                   |                       | (2)                        |
| 2016 | [54] | (1)                       |                     | (2)          |                         |                       | (1)               |                       | (2), (3)                   |
| 2016 | [55] | (1)                       |                     |              | (1), (3)                | (2)                   | (1), (2)          |                       | (2), (3)                   |
| 2017 | [45] | (2)                       |                     |              |                         |                       |                   |                       |                            |
| 2017 | [51] |                           |                     |              |                         |                       |                   |                       | (6)                        |
| 2017 | [47] |                           |                     |              |                         |                       |                   | (2)                   | (1)                        |
| 2017 | [82] |                           |                     | (1)          | (3)                     |                       |                   |                       | (2), (4), (6)              |
| 2017 | [87] |                           | (4)                 | (2), (4)     | (3)                     |                       |                   | (1), (2), (4)         | (2), (3), (4)              |
| 2018 | [72] |                           |                     | (5)          |                         |                       |                   |                       | (1)                        |
| 2018 | [83] |                           |                     | (1)          | (2), (3)                |                       |                   |                       | (2)                        |
| 2018 | [77] |                           | (2)                 | (2)          |                         |                       | (3)               | (1), (2)              | (1), (5)                   |
| 2018 | [56] | (1)                       |                     |              | (1), (3)                |                       |                   | (2)                   | (2), (3), (6)              |
| 2018 | [68] | (3)                       |                     |              | (3)                     | (2)                   |                   |                       | (2), (3), (4)              |
| 2018 | [65] | (3)                       |                     |              | (3)                     | (2)                   |                   | (2)                   | (2), (3), (4)              |
| 2018 | [66] | (3)                       |                     |              | (3)                     | (2)                   |                   | (2), (4)              | (1)                        |
| 2019 | [91] |                           |                     | (5)          |                         |                       |                   | (3)                   | (2)                        |
| 2019 | [84] |                           |                     | (1)          |                         |                       | (3)               | (4)                   | (1), (2)                   |
| 2019 | [50] |                           |                     |              |                         |                       |                   |                       | (2), (3), (4)              |
| 2019 | [64] |                           | (2)                 |              |                         |                       |                   | (3)                   | (1)                        |
| 2019 | [75] |                           | (1), (2)            | (1), (2)     | (2), (3)                |                       |                   | (3)                   | (2), (4), (6)              |
| 2019 | [85] |                           |                     | (1)          | (3)                     |                       |                   |                       | (2), (3), (4)              |
| 2019 | [57] | (1)                       |                     |              |                         |                       |                   |                       | (2)                        |
| 2019 | [74] |                           | (1), (2)            | (2)          |                         |                       |                   | (3)                   | (2), (5)                   |
| 2019 | [58] | (1)                       |                     |              |                         |                       |                   |                       | (1), (2)                   |
| 2019 | [88] |                           |                     | (2), (4)     | (3)                     | (2)                   |                   |                       | (2), (3)                   |
| 2019 | [63] | (2)                       |                     |              | x                       | x                     |                   |                       | (1), (4)                   |
| 2019 | [71] | (4)                       | (1)                 | (2), (3)     |                         |                       |                   | (1)                   | (1), (2)                   |
| 2019 | [49] |                           |                     |              | (2), (3)                |                       |                   |                       | (2), (3)                   |
| 2020 | [78] |                           | (2)                 | (2)          | (3), (4)                | (2)                   |                   |                       | (2), (3), (4)              |
| 2020 | [48] |                           |                     |              | (2)                     | (1)                   |                   |                       | (2), (4)                   |
| 2020 | [67] | (3)                       |                     |              | (3)                     | (2)                   |                   |                       | (2), (3)                   |
| 2020 | [73] |                           | (1)                 | (2)          |                         |                       |                   | (1), (2), (5)         |                            |
| 2020 | [69] | (3)                       |                     |              | (3)                     | (2)                   |                   |                       | (2), (3)                   |
| 2020 | [76] |                           | (1), (2)            | (2)          |                         |                       |                   | (2)                   |                            |
| 2020 | [60] | (1)                       |                     |              | (1), (3)                | (2), (3)              | (3)               | (4), (5)              | (1)                        |
| 2020 | [79] |                           | (2)                 |              | (1), (3)                | (2), (3)              | (3)               | (4)                   | (2)                        |
| 2020 | [70] |                           |                     | (2), (4)     |                         |                       |                   |                       | (1), (2)                   |
| 2021 | [80] |                           | (1), (3)            | (2)          |                         |                       |                   |                       | (2), (4), (5), (6)         |
| 2021 | [89] |                           |                     | (2)          |                         |                       |                   | (3)                   | (1)                        |
| 2021 | [59] | (1)                       |                     |              |                         | (1), (2)              |                   |                       | (1)                        |
| 2021 | [62] | (2)                       |                     |              |                         |                       |                   |                       | (4)                        |
| 2021 | [61] | (1)                       |                     |              | (3)                     | (2)                   |                   | (4)                   | (2), (3)                   |
| 2022 | [90] |                           |                     | (2)          |                         |                       | (3)               | (2), (4)              | (2)                        |

3) **EV travel related objectives:** Objectives associated with the CI planning implications with respect to the travel patterns can be distinguished into five categories. To start with, several papers [75,81–85] aim at minimizing the energy costs of transportation (1) required to reach the next charging station. This is addressed by penalizing the additional EV energy consumption with a certain electricity price. The minimization of the travel time (2) has also received great interest in recent literature. Two different approaches can be distinguished. Studies [54,73,76,78,86–88] incorporate the overall travel time by penalizing the travel time with certain costs. Papers in [75,77,80,89] exclusively include the additional travel time costs to reach the next charging station in the CI location optimization. Article [90] aims at minimizing the costs associated with the distance to the next charging station.

The work in [74] considers both the travel time costs to the next charging station and the opportunity loss costs for the taxi passenger if no electric taxi can arrive in time due to the rerouting for charging. Additionally to the overall travel time costs, the study in [71] considers minimizing the delay costs (3) caused by traffic congestion on the road network. The works in [87,88] include travel time costs and the expansion of the road network in their modeling framework. Both studies aim at finding the optimal placement of CI while minimizing the costs for new lanes and roads (4) along with other objectives. Article [70] considers distance costs to the next charging station as well as additional costs for road improvements. The minimization of travel related maintenance costs (5) is factored into the CI planning decision in [72,91].

### 3.2. Distribution network related objectives

Having discussed the TN related objectives, the following section will address the DN related objectives. The literature is classified according to five different categories, by distinguishing between the objectives related to:

- 1) the grid connection costs of the CI,
  - 2) the grid reinforcement costs,
  - 3) the grid operation costs,
  - 4) the electricity supply and
  - 5) the impact of EV charging on the DN.
- 1) *Grid connection related objectives*: The grid connection related objectives encompass all objectives aimed at minimizing the initial investment costs of connecting the CI to the DN. Four different objectives can be distinguished: the minimization of substation (1), transformer (2), feeder (3) and busbar (4) costs. The literature in [55,56,60,79] tries to find the optimal CI allocation by minimizing both the substation and feeder investment costs. The work [53] additionally considers the transformer costs. Articles [49,75,83] focus on both the transformer and feeder investment costs. While papers [61,65–69,81,82,85,87,88] solely consider the feeder investment costs in the optimization approach, article [48] aims at minimizing the transformer investment costs during the CI planning. In [78] both the investment costs for feeders and new busbars are included in the CI location optimization.
- 2) *Grid reinforcement related objectives*: Closely related to the investment costs of new grid components are the reinforcement costs incurred during or after the CI deployment. Note that both types of costs may not always be distinguishable from each other. Nonetheless, an attempt was made to delineate both cost components as best as possible, based on the given description in the literature. Paper [48] addresses the need for additional voltage regulation (1) in terms of minimizing the expected costs. The works in [53,55,61,65–69,78,88] focus on minimizing the reinforcement costs of substations (2). Long-term investment costs for both substations and voltage regulation induced by EV charging are considered in [59]. Articles [60,79] aim at minimizing both the substation and feeder (3) reinforcement costs.
- 3) *Grid operation related objectives*: Few studies include the operating costs of the additional required grid components in the CI planning approach. The work in [54] focuses on minimizing the annual operating costs of the substations (1), which were additionally installed for the CI placement. Paper [55] likewise includes the substation operating costs in the CI planning but additionally considers minimizing both the operating and maintenance costs for the newly installed feeders (2). Articles [60,79,84,90] aim at minimizing the operating costs of different distributed energy resources (3). While papers [60,84] aim at finding the optimal CI configuration to minimize the operating and maintenance costs of distributed generation units, operating costs in form of power curtailments are considered in paper [90] and the work in [79] includes energy storage degradation costs as operating expenses.
- 4) *Electricity supply related objectives*: Concerning electricity supply, we consider a division into five different objectives, namely: (1) the minimization of power generation costs, (2) the minimization/maximization of the energy purchase costs and energy sales revenues, (3) the minimization of the EV charging costs, (4) the minimization of the investments costs for other distributed energy resources and (5) the minimization of carbon emission costs. The generation costs are the production costs of electricity of the considered generation units in the respective papers. The energy purchase costs/energy sales revenues encompass the costs/earnings of purchasing or selling power from the electricity market to serve the total demand of the system. The charging costs, on the contrary, solely consider the costs directly linked to the charging demand itself. While in most cases the charging costs will be similar to the market price, the charging costs could differ depending on the strategy of the charging point operator. To start with, the article [71] tries to maximize societal welfare by minimizing the total generation costs of electricity. Study [86] also considers the total generation costs but additionally aims at minimizing the EV charging expenses paid by the EV driver. In papers [63,64,74,75,77,89,91] the charging expenses are considered as an important criterion for the CI layout. The work presented in [87] considers both the power generation costs, the purchase costs of electricity and the installation costs of new generation units in the joint planning of TN and DN. Paper [73] contemplates both the distributed generation costs and costs for purchasing electricity from the main grid while also taking into account additional carbon tax costs. Article [60] likewise aims at reducing carbon emission costs. The electricity purchase costs are considered in [65,66,90]. Paper [78] minimizes the purchase costs of both active and reactive power from the upstream grid. In [76] the aim is to minimize the annual expected energy costs of the DN, measured as the difference between purchase costs and earnings from selling surplus energy to the upper-level power grid. In [47] the service provider's perspective in the CI placement is considered by including the electricity purchase costs and charging sale revenues. The paper [66] considers the investment cost of photovoltaic (PV) power plants in the joint EV CI and PV planning approach. The investment costs of additional needed generation units are taken into account in work [84]. While articles [60,61] aim at minimizing the costs for the installation of wind and PV power plants, the research in [90] additionally aims at minimizing the costs for energy storage units. Installation costs for energy storage systems and distributed PV generation plants are considered in [79].
- 5) *Grid impact related objectives*: With uncontrolled EV charging potentially posing a variety of challenges to the power system, a majority of the reviewed studies address the issue of various grid impacts when planning the CI. A classification of six different objectives is considered. First, the works in [52,58,62,66,70,71,76,77,84] aim at minimizing the voltage deviation (1), associated with certain penalty costs. This is accomplished by intelligently placing the charging stations in the DN. Second, an even more popular approach is to minimize the grid losses (2) of the power system. While articles [49,52–54,56–58,60–62,70,71,77,79,90] aim at minimizing the total losses in the grid, the works in [72,81–85,91] solely focus on minimizing the additional grid losses incurred by the EV charging. The maximization of the grid reliability (3) is the third objective. Article [64] formulates a VRP index, with the goal of minimizing both voltage deviations and power losses as well as maximizing the DN reliability. The reliability index is formulated as the weighted sum of the system average interruption frequency index, the system average interruption duration index and the customer average interruption duration index. The approach in [55] also includes the power loss in the objective function but additionally aims at maximizing the DN reliability by minimizing the average annual unserved demand after outage. The work in [89] considers penalty costs for voltage deviations and addresses the DN reliability in form of penalty costs for the average energy not served. Article [80] uses the expected loss of energy caused by load curtailments as a reliability indicator for the DN. The work in [47] provides a profit maximization approach for charging service operators with the

aim of reducing penalty costs for violating power limit violations (4). Moreover, minimization of the DN loss and a load leveling goal (5) is included in paper [74]. Last, article [51] aims to maximize the EV penetration (6) without causing any congestion in the DN.

### 3.3. Charging infrastructure related objectives

The third category includes all objectives relating to the costs of the CI itself that cannot be assigned to the TN or DN. Although an attempt has been made to classify the various cost components as best as possible, it should be noted that it is often not possible to make a precise distinction between the different cost components as the transition is fluid and the costs are often only vaguely defined in the reviewed literature. The following six cost components are differentiated.

To start with, the works in [50, 51, 59, 60, 63, 64, 72, 79, 86, 87, 89, 91] focus on the minimization of the total installation/construction/build-up costs (1). When classified as total construction costs, the considered papers did not clarify or distinguish the different cost components of the CI; therefore, this category considers the total costs for the CI deployment and hence could encompass all or several of the CI investment cost components. Second, studies [47–49, 53–56, 61, 65–70, 74, 75, 78, 81–85, 88, 90] include the fixed investment costs of the CI (2) as one of the objectives to minimize, such as the CI equipment costs. The minimization of variable investment costs (3), such as the cost of adding charging plugs, is taken into account in [49, 54–56, 61, 65–69, 78, 81, 82, 84, 85, 88] and represents the third category of objectives. Moreover, the land costs (4) can be considered as an integral part of the total cost of new charging stations to be built and are therefore minimized in numerous studies such as [47, 48, 53, 62, 63, 65, 66, 68, 70, 74, 75, 78, 81–85]. Furthermore, papers [50, 70, 72, 74, 83] address the operating and maintenance costs (5) of CI in their planning framework. Note that several studies list the energy costs associated with the charging as operating costs. However, the charging costs were already dealt with in the DN related objectives and are therefore not considered in this category. Last, other costs (6), such as fees or labor costs, can also be found in recent literature [47, 56, 70, 75, 83].

## 4. Modeling approach for charging demand

Having discussed overall objectives for the CI planning problem in the previous section, this section focuses on how charging demand is modeled. Charging demand is here understood as the demand for a given charging service, typically framed in a space-time context. It concerns the CI location methodology and the modeling of capacity constraints. The latter can be based on queuing models or flow-capacity formulations also known from transportation models. An overview of the location method and queuing system used in each of the reviewed literature is illustrated in Tables 3 and 4.

### 4.1. Charging infrastructure location methods

For the optimal placement and sizing of charging stations, which depends on the charging demand, typically well-known models from the transportation modeling literature are used. In the following, we classify the reviewed literature as being node-based, flow-based and agent-based.

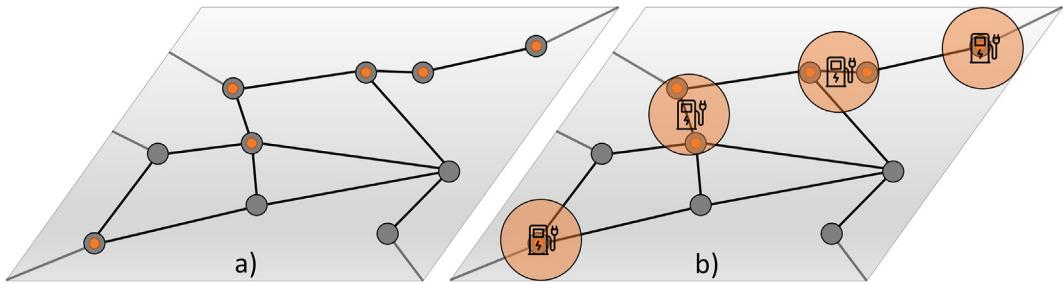
- 1) *Node-based approach:* The node-based approach assumes that charging demand can be represented by points in the geographical space. The notion of a 'point' for these approaches

typically refers to zones or a node in a directed graph for the TN. The node-based approach aims at locating charging facilities so that charging demand anchored to the nodes can be met. The node-based approach, when used in its basic form, typically refrains from considering network aspects of the charging demand. When applied in this basic form it requires a limited amount of data and thus has been a popular method that has been used frequently in the early literature. However, as the node-based model typically aims at predicting a match between locations and a fixed demand profile anchored to zones, it cannot measure potential detours associated with charging events. Hence, node-based models are generally simplistic in the way user charging behavior is modeled. A simplified illustration of the node-based approach is shown in Fig. 4, where the CI is aimed at covering a certain area of charging demand at nodes.

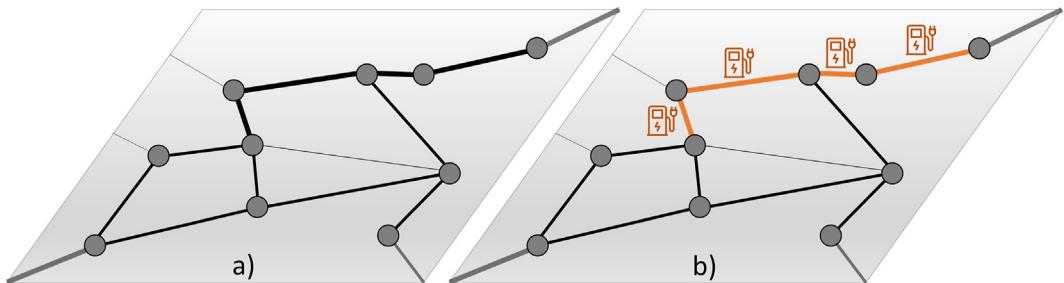
Historically, several methods have been used. The  $p$  – median model used in Refs. [81, 90] aims at locating  $p$  charging facilities to minimize the weighted distance between demand point and charging facilities. Set covering location models, as used in [50, 63], represent another node-based approach. Set covering models minimize the number of charging facilities to cover the charging demand, while restricting the allowed distance between charging facilities or between the charging facilities and charging demand respectively. A very similar approach is the node-based capacitated vehicle routing problem approach with fixed demand patterns as presented in [72, 91]. Another node-based approach, the maximum covering location model, is presented in [45, 46, 64] and is largely similar to a set covering location model with the exception that it seeks to locate charging facilities within a given distance to maximize the coverage of the demand. Hence, as opposed to the traditional approach these models avoid the assumption of fixed local demand. A node-based approach with uncertainty modeling and random sampling is used in [62, 89] respectively. Articles [48, 82, 84] use a zone-based formulation of the demand for the CI planning.

- 2) *Flow-based approach:* Contrary to the node-based approach, the flow-based approach considers demand in the form of traffic flows and typically aims at locating charging stations with the purpose of maximizing the traffic flow that passes through these stations. The flow-based approach is slightly more data-demanding compared to the node-based approach as it usually requires origin-destination data and flows in a directed network. Fig. 5 illustrates the flow-based approach in a simplified form where the CI is located at roads with the highest traffic flow.

Several approaches have been proposed. The flow-capturing model in many ways reassembles the approach for the set covering model except that the model seeks a maximal flow coverage and can be linked with traffic flows in the TN. It is commonly assumed that if a vehicle passes at least one charging station on its path, the flow is successfully covered. The works in [51, 56, 57, 59, 70] use a simple flow-capturing location model to optimally locate the CI. In [58] a flow-capturing model with service radius and waiting time constraints is considered to maximize the captured EV flow. A battery capacity-constrained flow-capturing model is introduced in [52]. The battery constraint allows to account for the fact, that a single station may be not enough on certain routes and multiple charging possessions are needed to enable the EV driver to reach its destination. The work in [60] integrates a flow-capturing location and user equilibrium traffic assignment model to optimally deploy the CI. In [53] another traffic assignment model is proposed to obtain equilibrium traffic flows in a TN with capacity-



**Fig. 4.** Simplified illustration of the node-based approach. An exemplary transportation network with a set of charging demand nodes (in orange) to be covered is shown in a). In b) the charging infrastructure, covering a certain area (orange circles), is placed to cover the demand at the nodes. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

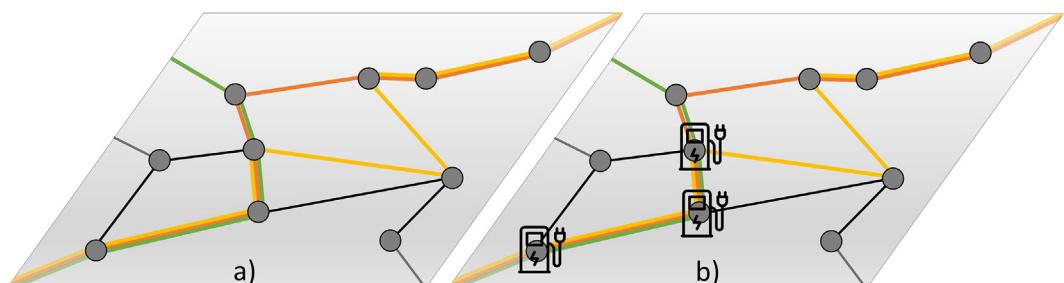


**Fig. 5.** Simplified illustration of the flow-based approach. An exemplary transportation network with different vehicle flows (indicated by the difference in line thickness) to be covered is shown in a). In b) the charging infrastructure is placed to cover a maximum of traffic flows.

constrained charging stations. A different flow-based equilibrium approach is introduced in [76] where congestions in the TN are modeled in parallel. The works in [54,55] introduce a user equilibrium traffic flow assignment model. Another popular approach in the literature is the so-called flow-refueling location model which accounts for the possibility that a single charging facility on a given path might not have sufficient capacity to capture the entire vehicle flow. An extended flow-refueling location model, which allows alternative driving paths from origin to destination, is introduced in [73]. A capacitated flow-refueling location model, which includes the service capacity constraints of the CI, is presented in [61,67,69,78]. The works in [65,66] propose a modification of the capacitated flow-refueling location model to enable the capturing of time-varying charging demand. Finally, in [68,88] a traffic assignment model with flow equilibrium constraints, based on the capacitated flow-refueling location model, is presented.

3) *Agent-based approach:* Agent-based approaches represent a different approach from node- and flow-based concepts and are driven by the general idea of representative prototypical users. Agent-based approaches allow a completely heterogeneous description of users and their charging situation. Consequently, the data requirements are potentially large as it could entail individual driving patterns, very specific user information and information regarding the charging decision. The benefit of agent-based models is the ability to represent the randomness that emerges from interactions of heterogeneous agents in complex systems with limited capacity. A simplified illustration of the agent-based approach with three individual tours is illustrated in Fig. 6, with the CI being placed at the locations with the most charging opportunities.

While the agent-based CI planning approach is widely used for isolated TN models, the literature today contains only a few examples of agent-based models applied to the combined TN and DN problem. Paper [74] introduces a multi-agent simulation



**Fig. 6.** Simplified illustration of the agent-based approach. An exemplary transportation network with three individual vehicle tours (indicated by colored paths) to be covered is shown in a). In b) the charging infrastructure is placed to cover the locations with the most charging opportunities, assuming that the vehicles stop at each node they travel through.

with three different types of agents: the electric taxi agents, the public charging station agents and the traffic node agents. Similar work is presented in [77] where the aim is to optimize the CI for electric taxis based on a multi-agent system. Various agents, such as the power grid agent, charging station agent and electric taxi agent, are considered in an event-based discrete simulation framework. Last, the work in [47] presents an agent-based simulator referred to as the 'EV Virtual city' to optimally locate CI and balance the benefits of the EV owner, charging station owner and grid operator.

#### 4.2. Queuing systems

Charging demand is subjected to capacity constraints at the different charging stations. Typically, the demand-supply relationships in agent-based models are modeled as part of a queuing system of which many variants exist. The most simple form is that of simple parametric Markov queues ( $M/M/s$ ) with a uniform arrival and service process. The advantage of this model is its closed-form representation, which makes it suitable for integration in mathematical programs. The disadvantage, however, is that it is based on a simple parametric model, which is unable to capture spatial and temporal variation in demand. Not only are arrival patterns different over time simply due to variations in the traffic pattern over the day, but the arrival patterns of one station are also affected by the arrival patterns of other stations. The combined arrival variation is very difficult to capture in a simple parametric queuing model. An alternative is to use non-parametric queuing models, e.g.  $G/G/s$  models following Kendall's notation. These models are essentially formed from data for observed arrivals and require that a demand simulator is integrated within the queuing system.

The reviewed literature can be classified into two main categories. The majority of papers do not consider such capacity constraints and hence discard the notion of queues [45,47,50,52,56,59,61–63,65–67,69,71–75,78,80–91]. A typical requirement for these systems is the absence of temporal dynamics and a very common approach is to consider an optimum that refers to a peak hour or a fixed time interval. This introduces the problem of translating an optimal solution that reflects 1 h to an optimum that reflects a full day or a full year. The second group of papers uses different types of queuing systems.  $M/M/s$  queuing systems, which are based on Poisson distributed arrival times and exponentially distributed service times, are used in [46,49,51,53–55,57,58,60,64,77]. Article [70] proposes  $M/M/s/N$  queuing. Compared to the  $M/M/s$  queuing system that assumes unlimited space for queuing, using  $M/M/s/N$  queuing constraints the capacity of the queuing system at  $N$ . The studies in [68,76] introduce an  $M/G/s$  queuing model, which allows for more general modeling of the service time. The work in [48] uses  $s$  times  $M/M/1$  queuing to model the capacity constraints of the CI.

#### 5. Application focus of the respective studies

This paragraph focuses on the application aspects of the CI planning problem. We do so by considering aspects related to:

- 1) the charging technology,
- 2) the optimization methodology,
- 3) the target area under study and
- 4) the scope of the case study.

In the following, we classify the respective studies according to the considered charging technology. The optimization methodology, the target area and the applied case study are considered

separately within each paragraph. Table 3 provides an overview of the analysis results for each study. Literature addressing the collaborative planning of CI and distributed energy resources (DER) is dealt with in a separate section and a summary of the findings is provided in Table 4.

##### 5.1. Placement of slow charging infrastructure

Only four papers address the optimal placement of slow CI when considering a combined TN and DN approach. Study [52] introduces a multi-objective approach based on data envelopment analysis for the optimal placement of slow CI. The optimization is solved by a cross-entropy algorithm and is tested on a coupled 25-node TN and 33-node DN test system. The proposed method reduces both power losses and voltage deviations while minimizing the EV traveling distances.

Article [86] proposes a game-theoretical approach for optimizing the placement of public CI for plug-in hybrid EVs in an urban area. The optimization is solved by an active-set algorithm and is applied to a coupled 24-node TN and subset of IEEE 118-bus DN.

The work in [54] also focuses on the siting and sizing of slow CI in urban areas but takes into account different types of charging locations such as charging in residential and office areas. The economically most favorable solution is obtained by comparing a suitable set of alternative plans. Moreover, the authors propose a multi-objective planning approach to be solved based on game theory. Though real load profiles are used in the study, the performance of the model is analyzed on a coupled test system consisting of a 24-node TN and IEEE 12.66 kV 33-bus system.

The paper in [62] formulates a multi-objective CI allocation problem for three different types of charging locations in urban areas: residential charging, charging at supermarkets and charging at road junctions. The model takes into account the uncertainty of both grid-to-vehicle and vehicle-to-grid charging with different charging powers (0.8 kW–19 kW). Even though the paper refers to fast charging when talking about charging rates of 8 kW and 19 kW, such charging rates are considered as slow charging according to our definition. The proposed approach is solved by differential evolution and Harris hawks optimization techniques and tested on a coupled urban TN and 11 kV 33-node radial DN. The results show that the variation of charging power does not exert a major influence on the results of the CI allocation.

##### 5.2. Placement of fast charging infrastructure

As can be seen in Table 3, the majority of studies focus on the optimal deployment of fast charging infrastructure (FCI) while neglecting other charging technologies.

- 1) *Fast charging deployment in urban areas:* Several papers focus on the deployment of FCI in urban environments. Study [53] introduces a decomposition-based multi-objective evolutionary algorithm to deploy roadside FCI in an urban area. The proposed collaborative planning model is tested on two different test scenarios, a coupled 20-node TN and modified 23-node 15 kV radial DN as well as a coupled 25-node TN and 54-node 15 kV DN. A proper trade-off between costs and EV driver's convenience is obtained.

Paper [83] introduces a NIO algorithm called binary lightning search algorithm for the optimal allocation of roadside FCI. Simulations for a multi-objective framework on the road network of Bangi coupled with a 47-bus Malaysian radial DN show that the suggested technique mainly benefits three stakeholders: the EV driver, FCI providers and the power grid.

**Table 3**

Methodical overview of the literature addressing the optimal planning of electric vehicle charging infrastructure.

| Type of charging | Ref. | Demand      | Queuing | Overall optimization methodology  | Target area        | Case study |
|------------------|------|-------------|---------|---|--------------------|------------|
| Slow charging    | [52] | Flow-based  | No      | Cross-entropy data-envelopment analysis   | —                  | T          |
|                  | [86] | Flow-based  | No      | Active set algorithm  | Urban              | T          |
|                  | [54] | Flow-based  | M/M/s   | Comparison of set of alternative plans & game theory                                      | Urban              | T          |
|                  | [62] | Node-based  | No      | Differential evolution & harris hawks optimization  | Urban              | T          |
|                  | [53] | Flow-based  | M/M/s   | Decomposition based multi-objective evolutionary algorithm                                | Urban              | T          |
|                  | [68] | Flow-based  | M/G/s   | MILP solved by deterministic branch-and-bound in CPLEX                                    | Highway            | T          |
|                  | [46] | Node-based  | M/M/s   | Ant colony optimization   | Res.               | M          |
|                  | [55] | Flow-based  | M/M/s   | Multi-stage search strategy   | Res. & comm.       | T          |
|                  | [58] | Flow-based  | M/M/s   | MINLP solved by multi-objective grey wolf optimizer                                       | Res.               | T          |
|                  | [67] | Flow-based  | No      | Data-driven distributional robust optimization approach based on $\varphi$ -divergence    | —                  | T          |
| Fast charging    | [91] | Node-based  | No      | MINLP solved by commercial solver in CPLEX  | Urban              | T          |
|                  | [72] | Node-based  | No      | MINLP solved by commercial DICOPT solver  | —                  | T          |
|                  | [59] | Flow-based  | No      | MINLP solved by graph-based cross-entropy algorithm                                       | —                  | T          |
|                  | [85] | Node-based  | No      | Mixed-integer SOCP solved in CPLEX  | Urban              | M          |
|                  | [74] | Agent-based | No      | Improved genetic algorithm  | Urban              | T          |
|                  | [73] | Flow-based  | No      | SOCP solved by Gurubi   | Highway            | T          |
|                  | [82] | Node-based  | No      | Genetic algorithm   | Urban              | R          |
|                  | [78] | Flow-based  | No      | MINLP solved by BARON solver in GAMS  | Urban              | T          |
|                  | [48] | Node-based  | M/M/1   | Integer linear programming solved by CPLEX & heuristic algorithm                          | Urban              | M          |
|                  | [83] | Node-based  | No      | Binary lightning search algorithm   | Urban              | R          |
| Mixed            | [75] | Flow-based  | No      | 2-level iterative optimization  | Urban              | R          |
|                  | [77] | Agent-based | M/M/s   | Multi-agent system (MAS) with multi-step Q( $\lambda$ )-learning and evidential reasoning | Res., ind. & comm. | T          |
|                  | [65] | Flow-based  | No      | Stochastic mixed-integer SOCP solved by branch and cut in CPLEX                           | Highway            | T          |
|                  | [81] | Node-based  | No      | Genetic algorithm   | Urban              | M          |
|                  | [49] | Node-based  | M/M/s   | Cooperative co-evolutionary genetic algorithm   | —                  | T          |
|                  | [69] | Flow-based  | No      | Single-level mixed-integer SOCP solved by CPLEX   | Res. & comm.       | T          |
|                  | [45] | Node-based  | No      | MINLP solved by branch-and-reduce optimization navigator (BARON) in GAMS                  | Urban & Highway    | M          |
|                  | [51] | Flow-based  | M/M/s   | Non-linear integer programming  | Urban              | M          |
|                  | [80] | Flow-based  | No      | Correlation analysis  | Res., & comm.      | T          |
|                  | [56] | Flow-based  | No      | Decomposition based multi-objective evolutionary algorithm                                | Res. & ind.        | T          |
| Unclear          | [57] | Flow-based  | M/M/s   | Genetic algorithm   | Urban              | T          |
|                  | [71] | Flow-based  | No      | Optimization based on Yen's algorithm   | —                  | T          |
|                  | [50] | Node-based  | No      | Conventional optimization   | —                  | T          |
|                  | [89] | Node-based  | No      | CSO-TLBO  | —                  | T          |
|                  | [64] | Node-based  | No      | Pareto dominance based CSO-TLBO   | Urban & highway    | R          |
|                  | [47] | Agent-based | No      | Bayesian game   | Urban              | M          |
|                  | [63] | Node-based  | No      | GIS-based multi-objective particle swarm optimization                                     | Urban & highway    | R          |
|                  | [88] | Flow-based  | No      | MILP solved in GAMS   | Highway            | T          |

comm. = commercial area; CSO-TLBO = Hybrid chicken swarm optimization and teaching learning based optimization; ind. = industrial area; MILP = Mixed-integer linear programming; M = Real case study for one of the transportation or distribution network; MINLP = Mixed-integer non-linear programming; R = Real case study for both networks, res. = residential area; SOCP = Second-order cone programming; T = Case study is based on test networks.

**Table 4**

Methodical overview of the literature addressing the collaborative planning of charging infrastructure and distributed energy resources.

| Type of charging | Co-planning element(s) | Ref. | Demand     | Queuing | Overall optimization methodology                       | Target area        | Case study |
|------------------|------------------------|------|------------|---------|--|--------------------|------------|
| Fast charging    | PV                     | [76] | Flow-based | M/G/s   | Surrogate-based optimization                           | Res., comm. & ind. | T          |
|                  | PV                     | [66] | Flow-based | No      | Generalized benders decomposition algorithm            | Highway            | T          |
|                  | DG                     | [84] | Node-based | No      | Non-dominated sorting genetic algorithm II             | Urban              | T          |
|                  | Wind, PV & ESS         | [90] | Node-based | No      | Mixed-integer programming solved by CPLEX              | —                  | T          |
|                  | Wind & PV              | [61] | Flow-based | No      | Mixed-integer linear programming                       | —                  | T          |
|                  | Wind & PV              | [60] | Flow-based | M/M/s   | Tchebycheff decomposition-based evolutionary algorithm | Urban              | T          |
|                  | PV & ESS               | [79] | Flow-based | No      | Natural Aggregation Algorithm                          | —                  | T          |
|                  | Wind                   | [70] | Flow-based | M/M/s/N | Multi-objective optimization solved by YALMIP          | Res. & comm.       | T          |
|                  | DG, lanes & feeder     | [87] | Flow-based | No      | Mixed-integer convex program solved by CPLEX           | Urban              | T          |

comm. = commercial area; ESS = energy storage system, ind. = industrial area, PV = photovoltaic, res. = residential area.

The studies in [81,82] propose a mixed-integer non-linear programming problem to determine the optimal location and capacity of the FCI in urban areas which is solved by a genetic algorithm. The presented approach is applied to three districts of the northwest area of Tehran and assumes a superimposed 13-bus DN. The work in [81] concludes that the EV energy loss costs and DN loss costs are the dominant part of the planning

problem and significantly influence the optimal location of the FCI. The analysis in [82] suggests that the optimal layout of the FCI is mainly influenced by different electric load scenarios, the EV circulation and EV users' charging preferences.

A mixed-integer linear programming model, solved by commercial solvers, is introduced in [78] to determine the optimal FCI layout in urban areas. The approach is applied to both a

small-scale test system, consisting of a 6-bus DN coupled with a 5-node TN and a large-scale system, which couples a 24-node TN with a 62-bus DN. Results demonstrate that the proposed model can be used for semi large-scale systems, with the ability to mitigate harmonics and compensate reactive power in the power grid.

Article [75] introduces a novel two-level FCI planning method based on dynamic real-time data. The simulation platform is applied to the road network of Beijing and for different DNs. The proposed framework simultaneously optimizes the economic interests of charging operators, while satisfying EV users' charging preferences and ensuring both traffic efficiency and power grid safety.

Different two-stage FCI planning approaches for urban areas are presented in [48,51]. In work [48], integer linear programming is used to determine the optimal locations of the FCI under consideration of the queuing time in a first step. A heuristic approach is applied in a second stage to estimate the number of charging poles. The authors also provide two FCI expansion models that can efficiently expand the charging network to accommodate increasing EV charging demand in the future. The discrete event simulator is tested on the urban area of Montreal, divided into 19 zones, and an IEEE 33-bus test system. The paper [51] introduces a two-stage planning method to minimize the annual costs of the system and 'shave' the EV peak demand. In the first stage, the evaluation model analyses the ability of the DN to serve the EV penetration and shifts shares of EV home charging demand to public fast charging. In the second stage, the costs to serve the demand are minimized while satisfying queuing and service time. The proposed approach is formulated as a non-linear integer programming model and applied to a coupled 20-node TN and 23-node DN. The analysis indicates that no major grid reinforcements are needed for an EV penetration up to 30% and that the model allows investors to decide on the trade-off between the overall annual costs, the EV users' charging convenience and proper pricing.

- 2) *Fast charging deployment in specified urban districts:* Few studies focus on certain areas in the urban environment. The deployment of FCI in residential areas is addressed in the works [46,58]. Ant colony optimization is used in [46] to solve the model. The validity of the method is presented for a residential area of the Tianjin development zone in China, coupled with an IEEE 69-bus test system. The work in [58] proposes the use of multi-objective grey wolf optimization with fuzzy satisfaction-based decision making for allocating FCI in residential areas. Using a superimposed 25-node TN and modified 123-bus DN, the authors conclude that the choice of service radius and waiting time exert a major influence on the CI planning results and that the proposed approach enables decision makers to decide on a proper trade-off between power losses, voltage deviations and served EV flow.

Articles [55,69] focus on the allocation of FCI in residential and commercial areas. Paper [55] introduces a multi-stage search strategy and applies the proposed method on a coupled 24-node TN and 54-bus 15 kV DN. The multi-objective framework provides a proper trade-off between costs, CI utilization and grid reliability. Study [69] proposes a robust chance-constrained programming approach for the optimal placement of FCI. The initial bi-level approach is reformulated into a single-level mixed-integer second-order cone programming model, solved by CPLEX. Simulations on a superimposed 24-node TN and 14-node 110 kV DN illustrate that the expected improvement of EV driving ranges in the future will lower investment costs and that AC power flow simulations provide more accurate planning results compared to DC power flow analyses.

Article [80] proposes a novel reliability-oriented multi-objective planning model for FCI in residential, recreational and commercial areas. Simplified reliability correlation analysis is used to solve the proposed approach efficiently and simulations on a non-specified TN superimposed with an IEEE 24-bus DN are presented. The authors conclude that the implementation of EV charging and discharging management strategies benefit the reliability of the DN but have a detrimental effect on the TN.

- 3) *Fast charging deployment on highways:* The allocation of FCI for long-distance travel is another focus area in the CI planning literature. The work in [68] tackles the optimal planning of FCI along a highway based on mixed-integer linear programming, which is solved by a branch-and-bound method. The model is applied to a coupled 25-node highway TN and 14-node 110 kV high voltage DN and it is shown that several inputs, such as the EV population, the feeder capacities, the driving range and the state of charge (SoC) exert a significant influence on the planning results. Using the same case study, the work in [65] introduces a stochastic mixed-integer second-order cone programming model, solved by the branch-and-cut method, to find the optimal layout of FCI on highways. The authors conclude that considering both networks leads to investment decisions that are more economically viable. Work [73] introduces an interdisciplinary second-order cone programming model to optimize EVs' driving paths and the FCI on highways. The proposed method is efficiently solved by an iterative column generation algorithm and tested on both a 25-node highway TN coupled with a 110 kV DN and a 108-node TN superimposed with a 110 kV DN. The simulation results indicate that proper routing of EV traffic flows can improve social welfare and promote renewable generation integration and that optimizing over multiple objectives results in trade-offs between the power grid's and EV driver's benefits respectively.

The work in [45] introduces another two-stage FCI allocation methodology formulated as a mixed-integer non-linear programming problem. Solved by the branch-and-reduce optimization navigator in GAMS, the proposed method is applied to three case studies to demonstrate the feasibility and robustness of the model and the ability in dealing with different network topologies. The urban test case consists of a coupled 20-node TN and 15 kV 23-node DN, while Ontario's 401 highway is selected for the highway case study. Results show that the FCI layout is highly sensitive to the selected service range of the FCI, defined as the area the charging station needs to cover.

- 4) *Fast charging deployment for non-private EVs:* While most studies try to find the optimal CI for privately owned EVs, electric taxis, electric buses and freight EVs will to an even higher degree rely on an efficient FCI. Articles [74,77] address the FCI deployment for electric taxis. Paper [74] introduces an optimized genetic algorithm to allocate the FCI in an urban environment. A multi-objective framework embedded with multi-agent charging demand simulations is presented and applied to a coupled 24-node TN and 10 kV 33-bus DN. The authors conclude that the retailer's charging strategy has a great influence on the profitability of the FCI and thus needs to be carefully analyzed. In Ref. [77] multi-agent simulation with multi-step  $Q(\lambda)$ -learning is used to estimate the charging demand of electric taxis. Hereafter, the FCI locations in different residential, business and industrial districts are optimized under multiple objectives using evidential reasoning. Results for a coupled 108-node TN and 110 kV DN show that the proposed model provides benefits for the EV driver and DSO by reducing the charging waiting and travel times and power losses as well as by improving the voltage profiles.

The work in [85] formulates a novel mixed-integer second-order cone programming approach for large-scale FCI planning

for electric buses. The multi-stage optimization takes into account the growing charging demand at different stages and approximates a globally optimal solution. Numerical evaluations for a real TN in Shenzhen (China) superimposed with a 110 kV DN show that allowing higher investments in the early stages can decrease deployment costs in the long run.

The FCI planning problem along with the optimal routing of EVs for freight transportation is addressed in [91]. Taylor series is used to linearize the mixed-integer non-linear programming problem, which is then solved by commercial solvers. Tests are conducted on a 34-node DN and 123-node DN test system coupled with a TN. Similar to article [91], paper [72] investigates the integrated planning of EV routing for merchandise transportation and FCI locations based on a mixed-integer non-linear programming model which is solved by the DICOPT solver in GAMS. Various variations of superimposed TN and DN test systems are designed to evaluate the model performance. The authors conclude that the proposed methodology can achieve a proper trade-off between the optimal routing, the optimal FCI locations and the minimization of DN losses.

- 5) *Other:* Some studies cannot be assigned to any of the previously mentioned categories. In Ref. [67] a data-driven distributional robust optimization approach is presented. It is based on  $\varphi$ -divergence to optimal allocate the FCI at the coupling nodes between the TN and DN. The approach is tested on a 24-node TN coupled with a 110 kV DN.

A cross-entropy optimization algorithm is proposed in [59]. Graph-based modeling is used to allow the scaling of the method to different network coupling configurations and temporal resolutions. The computing efficiency of the proposed approach is validated on a synthetic network, coupling a 25-node TN and IEEE 123-node distribution test feeder.

The work in [49] proposes a scenario-based planning framework for simultaneous FCI sizing and siting and DN reconfiguration. A cooperative co-evolutionary genetic algorithm is employed to solve the problem. A 24-node TN is coupled with two different DN, an IEEE 33-bus and an IEEE 69-bus system, to evaluate the model. By including the possibility of network reconfiguration in the planning framework the DN losses are reduced and voltage profiles are improved.

### 5.3. Placement of mixed charging infrastructure

Article [57] presents a fuzzy multi-objective optimization approach, solved by a genetic algorithm, for the optimal siting and sizing of both slow charging and fast charging facilities. Simulations on a coupled 25-node TN and 33-node DN illustrate that the model is able to balance the two conflicting objectives of maximizing the captured traffic flow and minimizing the power grid losses.

The optimal placement of slow and fast CI is further addressed and solved by using a hybrid chicken swarm optimization and teaching learning based optimization approach in [64,89]. While [89] formulates the problem as a single-objective framework, multi-objective optimization is used in [64]. Furthermore, 2-stage planning is applied in [64]. While a coupled 25-node TN and 33-node DN is used as a test scenario in [89], a real case study of the superimposed highway TN and DN in Guwahati city (India) is applied to verify the proposed approach in [64]. Fuzzy decision making can select between Pareto-optimal solutions in [64] and the results in [89] indicate that the proposed algorithm is applicable to real-world problems.

Another work in [63] aims at finding the optimal location of slow and fast CI and considers AC and DC chargers with different charging powers. GIS-based particle swarm optimization is

proposed to solve the multi-objective planning framework. Simulations are carried out for the surrounding highway TN of the Changping district in Beijing. The construction of CI illustrates a mutually reinforcing relationship with the EV uptake, demonstrating the importance of CI for a successful EV market penetration.

Slow charging, fast charging and battery swapping are taken into account in paper [56]. A multi-objective and multi-stage collaborative planning model is proposed to locate the different charging solutions in residential and commercial areas. A decomposition-based multi-objective evolutionary algorithm is used to find the non-dominated solution to the problem. Tests on a coupled 25-node TN and 54-node DN show the effectiveness of the model.

The work in [71] proposes a novel placement method based on Yen's algorithm for FCI and battery swapping stations while considering grid impacts and traffic congestions. A case study on a coupled 25-node TN and IEEE 30-bus DN is conducted and shows the ability of the model to reduce the total costs of both systems.

Paper [50] introduces conventional optimization with a DN reliability check to determine the location for both slow and fast charging stations. A test TN coupled with a standard 6-bus test DN is used to evaluate the model. The results show that including the power system reliability check in the planning approach alters the allocation of CI and results in higher overall placement costs. An outage critically ranking is introduced as well to guide DSOs on grid reinforcement investments.

To optimal deploy level 1 – 3 chargers at different urban locations, such as residential areas, business areas, supermarkets, restaurants and shopping centers, article [47] proposes a multi-stage charging placement strategy based on a Bayesian game which takes into account the interaction of different stakeholders. The proposed method is applied to the TN of the San Pedro district of Los Angeles superimposed with an IEEE 118-bus DN test system. The simulations illustrate that the charging station placement is highly consistent with the traffic flow of EVs.

### 5.4. Collaborative planning of charging infrastructure

As previously discussed, large-scale EV charging infrastructure can have a detrimental impact on the DN. However, EVs can also interact positively with the DN by providing ancillary services or increasing renewable energy integration in the power system [92,93]. To this end, optimal coordination and operation between the TN and DN are essential [94–96]. While this work focuses on the optimal planning of CI by combining TNs and DN and thus does not address the optimal operation and coordination between both networks to achieve such benefits, there are several studies that consider the collaborative planning of EV CI and different DER to reduce the burden on the grid and provide economic and environmental benefits to the system.

Studies [84,87] aim at the optimal collaborative planning of EV CI and non-specified distributed generation. A mixed-integer non-linear programming approach, solved by non-dominated sorting genetic algorithm II, is introduced in [84]. The planning approach is framed as a multi-objective optimization to simultaneously deploy FCI and additional needed distributed generation units in urban areas. The combined planning approach is applied to a test case of an urban area with 180 zones, superimposed with a 118-bus DN. Compared to the individual planning of FCI and distributed generation units, the article demonstrates that the EV users' costs and the power loss of the grid can be significantly decreased. Article [87] proposes a mixed-integer convex programming approach for the optimal siting and sizing of EV CI, distributed generation and new transportation lanes and distribution feeders. The model is

tested under four different traffic scenarios on a coupled 10-node TN and 20-node DN. The results indicate that the approach is able to minimize investment costs under traffic and power flow constraints on small-scale networks.

The works in [66,76] address the optimal planning of EV FCI and PV power plants. While the work in [76] focuses on residential, commercial and industrial areas, paper [66] addresses the planning of FCI on highways. In [76] the approach is framed as a bi-level programming model and solved by a surrogate-based optimization algorithm. The case study on a coupled 13-node TN and 7-bus 110 kV DN indicates that an optimal pricing strategy increases the utilization of the CI and reduces queuing times by balancing the charging demands across different locations. Paper [66] suggests a two-stage stochastic programming approach. A generalized Benders decomposition algorithm is applied to solve the mixed-integer second-order cone program. A 25-node highway TN coupled with a 14-node 110 kV DN is used to demonstrate the effectiveness of the model to reduce the total investment and operating costs of the system.

The combined planning of EV CI and PV power plants is also addressed in articles [60,61], with additional consideration of the planning of wind power generation. Paper [61] proposes mixed-integer linear programming to obtain optimal locations and capacities of the FCI and renewable energy sources. Implemented on a 25-node TN coupled with both a 14-bus and 33-bus DN, the results indicate that including renewable energy resources in the initial planning phase can lower grid impacts and increase the captured traffic flow. The work in [60] implements two-stage stochastic programming with k-means clustering for the collaborative DN planning, solved by a multi-objective Tchebycheff decomposition-based evolutionary algorithm. Results on a coupled 25-node TN and 54-bus DN show the ability of the model to achieve both economic and environmental benefits for the system.

The optimal planning of battery storages is further included in works [79,90]. Paper [90] introduces a mixed-integer programming approach for the optimal planning of FCI with wind and PV generation and battery storage systems. The model is tested on a coupled 25-node TN and 33-node DN and the results indicate that the proposed model is able to increase renewable energy penetration rates and improve the system voltage. The work in [79] focuses on the optimal siting and sizing of shared EV CI, solar-based generation units and battery storage systems. Scenario analysis is used to consider the stochastic nature of the EV loads. The mixed-integer non-convex optimization problem is solved by natural aggregation algorithm and validated on a coupled 54-node DN and 25-node TN.

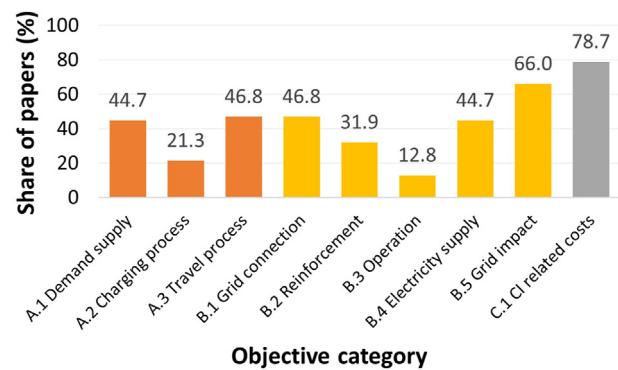
Article [70] proposes multi-objective optimization for the collaborative planning of EV CI and distributed wind generation in residential and commercial areas. The approach is evaluated through two case studies of a 24-node TN coupled with a 53-bus DN and 123-bus DN respectively. It is shown that power losses and voltage deviations can be significantly reduced.

## 6. Summary and discussion

Based on the review of the literature we here provide a discussion with respect to the state of research and its limitations. Specifically, we frame this discussion with respect to the above classification of the literature.

### 6.1. Planning objectives

As previously outlined, the majority of literature treats the CI planning problem as a multi-objective optimization approach. Fig. 7 displays the share of studies addressing the different categories of objectives as classified in Fig. 3.



**Fig. 7.** Share of studies addressing different planning objectives. The different sub-categories of planning objectives, as classified in Fig. 3 are listed on the x-axis. For each category, the share of papers is calculated separately and illustrated on the y-axis.

According to Figs. 7, 78.7% of the reviewed literature is concerned with the minimization of costs that can directly be linked to the CI deployment. Moreover, 66% of the articles aim at mitigating grid impacts through the optimal planning of the CI. However, when studying the respective objectives in Table 2 in more detail, it is notable that the majority of these studies only aim at minimizing the system losses. In light of the existence of far more severe grid impacts, e.g. such as the overloading of grid components, voltage imbalances or the EV impact on system security, it is questionable if grid losses will play an important role in real-life CI planning. In particular when considering the complexity of the planning process and its subordinate importance for the DN. Required grid reinforcement and grid connection costs are considered to be of high importance from a DSO perspective. However, this issue is only taken into account in less than 32% and 47% respectively of the reviewed papers. Surprisingly, important features such as the EV demand satisfaction or charging and travel process convenience related factors are only explicitly addressed in the objective function for the CI planning optimization by 44.7%, 21.3% and 46.8% of the papers. The practical relevance and feasibility of the CI deployment methods presented in the literature thus remain debatable, especially with regard to the importance of the selected objectives for practice-oriented planning.

### 6.2. Modeling of the demand side

The demand side of the charging problem is concerned with the modeling of charging demand from the user perspective. This involves, as an example, trade-offs between waiting time and costs and will typically vary spatially as well as temporally. The literature has been reviewed with respect to how demand for stations is modeled in terms of location methods and how capacity constraints are implemented, typically by means of queuing systems. Both determinants have wider consequences for the ability to capture a realistic system behavior.

Table 5 provides a summary of the differences between the node-based, flow-based and agent-based location methods. As

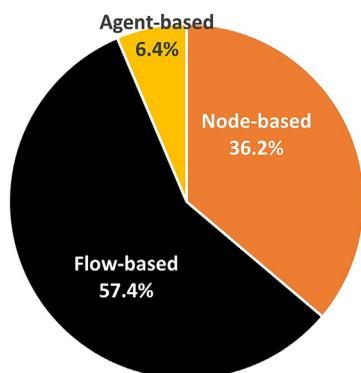
**Table 5**  
Comparison of the reviewed location methods.

| Criteria                    | Method     |            |             |
|-----------------------------|------------|------------|-------------|
|                             | Node-based | Flow-based | Agent-based |
| Data requirement            | Very low   | Low        | Very high   |
| User behavior modeling      | —          | —          | +           |
| Representation of demand    | —          | —          | +           |
| Most suitable target area   | Urban      | Highway    | Both        |
| Most suitable charging type | Slow&Fast  | Fast       | Slow&Fast   |

previously mentioned the node-based approach is the most favorable method in terms of data requirements followed by the flow-based approach since both methods are based on aggregated data. The agent-based approach is based on individual user behavior and thus exhibits the highest data requirements. However, the differences in data requirements translate directly into the ability of the models to represent user behavior and charging demand with the node-based approach suffering from most limitations in that respect, followed by the flow-based method. The node-based approach is only able to mimic a static vision of the charging demand and might often fail to present a realistic picture of user behavior as the EV user might not want to drive to the charging station just to charge the vehicle. The flow-based method is able to represent a more realistic picture of demand by accounting for vehicle flows but assumes the EV charging will take place during the trip, which might be only realistic for FCI. While the node-based approach therefore has advantages in urban environments, the flow-based location method might be more suitable for CI planning on highways [31]. The agent-based approach can be applied for every target area and charging type and is clearly the most favorable one according to most decision criteria, with the only barrier being the requirements related to data.

Therefore, from an ideal model perspective, the charging demand is formed from the bottom up by heterogeneous agents. These agents are different as a consequence of different demand preferences and differences with respect to their socio-economic status. Most notably, however, the agents possess different EVs with different driving ranges, different initial and final SoC levels and different charging speeds. The combined variability across these different attributes has an important effect on the charging demand for which a similar kind of space-time variability is expected. Fundamentally, it underlines the importance of characterizing demand as probability distributions rather than averages. This is even more important when considering the CI as an integral part of a power grid as in most countries power grids are rarely stressed beyond their capacity levels. Hence, the important requirement of a demand model is to be able to measure extremes and peaks to be able to handle even rare event load scenarios. Despite the arguable importance of representing demand as distributions and accounting for heterogeneity, the literature is surprisingly dominated by flow-based and node-based approaches as illustrated in Fig. 8.

As can be seen, with 57.4% the majority of studies apply flow-based approaches that use the notion of homogeneous flows. 36.2% apply a node-based approach and with 6.4%, only a few studies focus on a detailed agent-based modeling approach. Going a bit more into details, it is clear from the literature that conventional programming approaches have been and still are popular.



**Fig. 8.** Share of studies using different modeling approaches to locate the charging infrastructure, namely node-based, flow-based and agent-based methods.

However, these models tend to frame problems with respect to restrictions that are often deterministic and linear. As an example, many of the applications where queuing models are involved, use linear approximations of the queuing process and consider simple average waiting time as an objective. This is a serious limitation when considering combined problems because typically the design of DN systems is based on the ability to serve peak situations to avoid congestions as discussed above. Hence, rather than considering what is optimal from an average perspective, systems should be designed to serve the tails of the waiting time distributions and the tail of the power load distribution.

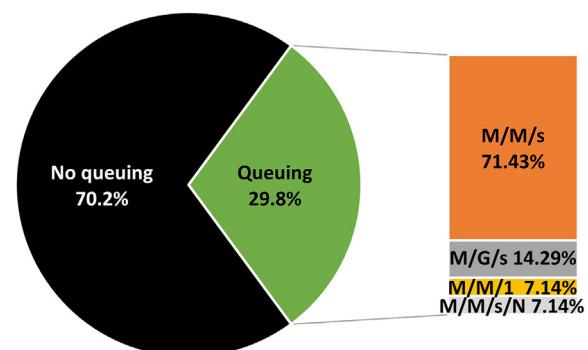
The way queuing systems are considered is linked with this issue. As illustrated in Fig. 9, with almost 72% the majority of models that apply queuing systems use simple M/M/s systems with constant arrival and service processes. This makes these models inappropriate as a means to model temporal variations and handle peak loading during the day or the year.

Another issue in the context of charging demand modeling is the initial selection of the SoC. The vast majority of the reviewed papers optimize system performance over a fixed horizon, e.g. 24 h or less. In order to predict demand, it is required that assumptions regarding the initial SoC are defined prior to the optimization. In many of the papers, these assumptions are quite simple and will in some cases correspond to setting a single initial SoC level, while in other cases, correspond to sampling from a normal or uniform distribution. However, these inputs cannot be classified as a 'steady-state' SoC level for EVs. Hence, there is a risk that such simple assumptions may lead to transient behavior in the optimization or simulation model that uses these inputs.

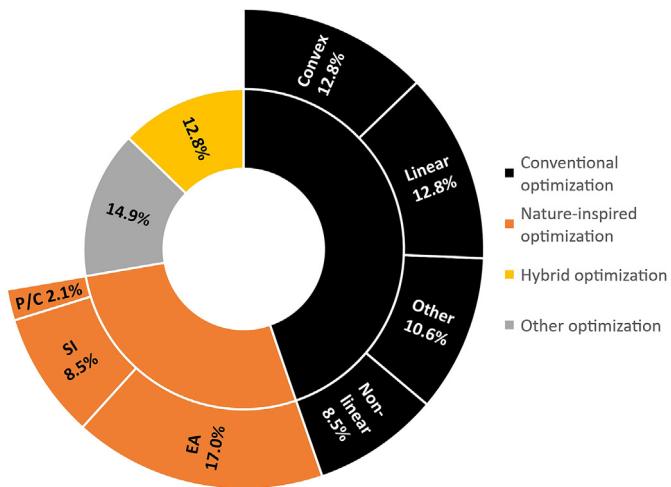
### 6.3. Optimization methodology

In Fig. 10 the reviewed literature is classified according to the optimization methodology. The studies are split into four upper categories: (1) conventional optimization approaches, (2) NIO algorithms, (3) hybrid optimization methods and (4) other optimization solutions. The conventional optimization approaches are divided into linear, non-linear, convex and other types of problems which can be solved by conventional mathematical solvers. NIO algorithms are here differentiated in evolutionary algorithms (EA), swarm intelligence (SI) based algorithms and physics and chemistry based algorithms (P/C). As can be seen, conventional optimization algorithms and NIO are those that are most widely used to solve the CI planning problem.

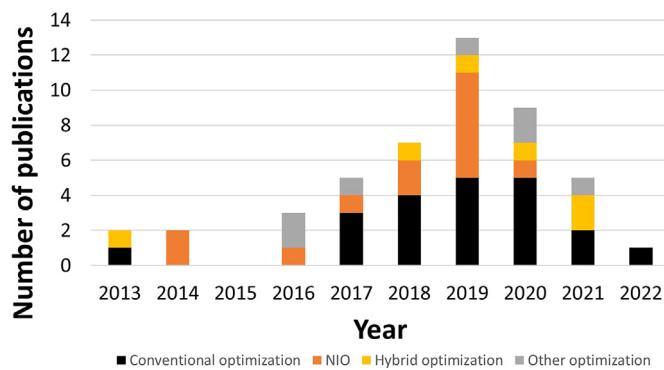
Fig. 11 illustrates the number of publications for each category of optimization technique published between 2013 and 2022. Starting



**Fig. 9.** Share of studies neglecting and using queuing theory for electric vehicle charging infrastructure planning. Papers using queuing theory are further analyzed by the type of queuing system employed.



**Fig. 10.** Share of studies using different optimization methodologies. The optimization methodologies illustrated in Table 3 and Table 4 are categorized in conventional, nature-inspired, hybrid and other optimization algorithms.



**Fig. 11.** Number of publications addressing the optimal planning of electric vehicle charging infrastructure in integrated transportation and power distribution networks in the years 2013–2022. The number of publications is further classified according to the applied optimization methodology. Conventional, nature-inspired, hybrid and other optimization approaches are colored in black, orange, yellow and grey respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

in 2017, the research regarding the planning of CI for combined TN and DN systems has gained increasing popularity with as many as 13 publications in the year 2019. While NIO algorithms have been applied in the entire period from 2014 to 2020, conventional optimization and hybrid approaches have gained ground after the year 2017. When looking at the publications for the year 2021 we can see an increase in the use of hybrid approaches. Nonetheless, when looking at the total number of publications, it becomes apparent that the combined view with respect to CI planning is still scarcely addressed in the literature.

A conclusion with regard to the optimization methodology is that much of the research seems to be fairly incremental and that many applications focus on small-scale problems. It is a tendency that many papers increment research by slightly changing the optimization methodology. However, there is a less critical view on the fact that most of the input assumptions are by and large uncertain. So while it may be possible to guarantee properties for a given optimal solution, based on possible model simplifications (e.g. linearization of functions) and assumptions, the practical value of such studies is often limited.

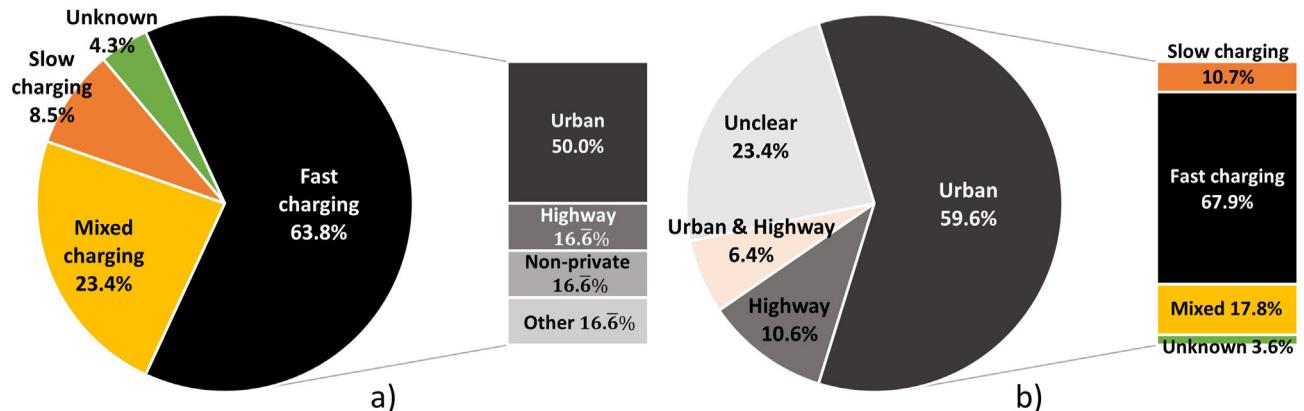
#### 6.4. Type of charging and area under study

**Fig. 12** illustrates the share of studies classified according to the deployed charging technology in a) and according to the target area in b). The literature addressing specific districts of urban areas as shown in Table 3 are defined as urban area studies. In **Fig. 12 a)**, the literature concerning the planning of FCI is further analyzed according to the target area under study and the type of EV. In **Fig. 12 b)**, the literature focusing on urban environments is analyzed in more detail regarding the considered charging technology.

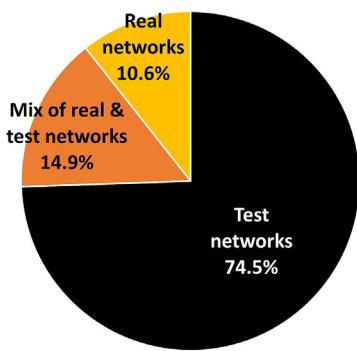
As can be seen in **Fig. 12 a)**, almost two-thirds of the reviewed studies focus on the planning of FCI, while only 8.5% focus on the deployment of slow CI. Just 23.4% of the reviewed literature takes into account different types of charging technologies. For FCI planning studies, half of the papers focus on urban areas, while the deployment of FCI on highways, for non-private EVs and ‘other’ account for only one-sixth of the studies each. **Fig. 12 b)** illustrates that almost 60% of the reviewed literature focuses on urban environments, while only 10.6% of the papers address the location problem on highways and 6.4% for combined urban and highway systems. When taking a closer look at the charging technology for urban areas, it is revealed that more than two-thirds of the studies focus on the deployment of FCI. These findings suggest that there is a clear lack of research that seeks to cover a combination of slow and fast charging options. While the placement and sizing of FCI for highways or non-private EVs such as electric busses, taxis or freight transportation constitutes a relevant challenge, the extensive focus on public FCI for private EVs in urban environments is more questionable. A large share of the public charging demand could be met by slow destination charging [97]. Hence, including both slow and fast charging options in the optimization approach would ensure that the EV charging demand can be met in a more cost-efficient way. Hence, a better understanding of mixed charging options as a means to understand the implication for the DN and how the demand is distributed among the different charging options and locations is a relevant and largely unexplored research area. A second conclusion is that it is evident that hybrid TN and DN based CI planning has mainly been applied to urban areas. There is a clear gap in the literature with respect to papers addressing the coupled planning view for sub-urban areas, for rural areas and for highway systems. Travel behavior and DN impacts might differ significantly in those areas, in particular, because highway systems may exhibit large variation in demand over time and for very large stations.

#### 6.5. Case study

In **Fig. 13** we present a breakdown of the types of case studies used in the reviewed literature. With 74.5% the majority of studies only consider a combination of transportation and distribution standard test networks. 14.9% of the reviewed literature uses a combination of real and test networks, with one of the TN or DN being based on a real use case. Less than 11% apply their methods to a real case study where both the DN and TN are modeled based on a real use case. Those findings reveal that most of the reviewed literature is lacking real data and focus on theoretical approaches for CI planning. Concerns in that respect are the ability to provide optimal solutions and the applicability for large-scale deployment. Further to this, many existing approaches may not be desirable and feasible for practical use, due to a lack of understanding of which objectives are most important. CI planning in practice is likely limited by numerous real-world constraints that relate to data and lack of these. Information regarding space availability is one example.



**Fig. 12.** Share of studies focusing on a specific type of charging and area. In a) the literature is first analyzed according to the type of CI, namely slow, fast, mixed or non-specified charging. The fast charging literature is further categorized according to the study focus- CI planning for private vehicles in urban areas or highways or CI planning for non-private vehicles. In b) the literature is classified according to the area under study - either urban, highways, both urban and highways or unclear. Studies focusing on the deployment of CI in urban environments are further broken down by the type of charging.



**Fig. 13.** Share of studies using different types of case studies. Test networks refer to standard test networks readily available in literature. Mix of real and test networks refer to one of the distribution or transportation network being based on a real case study and real networks refer to the literature where both the transportation and distribution network are modeled with real-world data.

## 7. Future directions of research

Based on the discussion of the current state of research, we identify five research gaps that, when combined with a problem perspective, lead us to identify several directions for future research.

First, concerning the planning objectives, there is a strong emphasis on objectives that relate to, e.g. the minimization of grid impacts in the form of grid losses and the minimization of CI costs. On the contrary, there is only little focus on important implications for charging operators and DSOs, such as grid congestion and required reinforcement costs to prevent overloading of specific grid equipment when deploying the CI. A reason for this, as we argue in the discussion, is likely that the later challenge requires a different perspective, which fits poorly with deterministic cost minimization. The problem of considering grid reinforcements is that the capacity of the system is largely determined based on rare event load scenarios and not the average consumption on a given day. Hence, the modeling of grid congestion and the analysis of available capacity to deploy the targeted CI requires a probabilistic perspective and data that can support the analysis of loading in space and time. To make the research more applicable to real-world CI planning, future research, therefore, needs to move towards probabilistic approaches to be able to address real needs and major concerns of several stakeholders.

Second, in line with the above discussion, the majority of the reviewed literature considers demand in very simplistic ways. Compared to related EV research areas where stochastic simulation of the charging demand is widely applied, such as EV CI planning in the TN or EV charging demand and DN impact analysis [98–100], the majority of the reviewed models for CI planning on coupled TN and DN are based on averages and deterministic perspectives. This does not allow the representation of demand as a probability distribution that varies geographically and temporally. Clearly, detailed demand-side representation is overshadowed by the inclination to optimize a multitude of objectives across different stakeholders, which in turn leads to neglecting the bottom-up dynamics that are crucial for the assessment of capacity. Randomness and variability, which are required to enable a more realistic representation of the charging demand in space and time, are largely absent from the literature. Future research should therefore focus on a better description of the temporal variation. This requires a shift from the notion of steady-state equilibrium modeling to incorporate more flexible arrival and service processes. Another consequence of applying very simplistic demand-side models is that it becomes difficult to investigate the impact of smart charging strategies, which could help prevent grid congestions by reducing the needed grid connection capacity and could thus enable CI to be installed at locations with limited available capacity for new loads. These strategies require that the notion of time and geography are considered appropriately. The analysis of smart charging as a means to avoid grid congestions could simultaneously benefit the TN with more CI locations being available for deployment.

Third, future research should also challenge the trend of one-shot, multi-objective CI planning for a given year or scenario. The one-shot optimization rules out the possibility of strategically developing the DN over stages. Often it will be optimal from the DN perspective to bundle investments and move larger investments forward (or backward) rather than apply smaller investment packages. Therefore, future research should consider using sequential planning where the CI is optimized based on different TN related key performance indicators for different connection stages.

Fourth, the literature mostly leans towards the planning of FCI in urban areas. However, understanding how a combination of different types of CI with different charging powers can meet the future EV demand in a cost-effective manner and how the demand is distributed among the different types of CI, is key to increase

flexibility and economic efficiency. A 'one-size fits it all strategy' is inefficient in many situations because the demand for services varies and also because the installation costs of these are very different. Hence, future research should consider a variety of different charging technologies in the CI planning.

Fifth, the majority of publications heavily focus on planning approaches that are motivated by theoretical concerns rather than being relevant in practice. The reason for this is a clear lack of real data. Future research should put more emphasis on the data collection effort to address the CI planning for more realistic case studies. This would ultimately enable a better understanding of real-world needs and problems as well as a better prioritization regarding objectives during the CI planning.

## 8. Conclusion

This paper provides a comprehensive review of the literature addressing the optimal placement and sizing of EV CI for integrated TNs and DNS. First, we present a general overview of the CI planning problem when considering both networks. Next, we propose a detailed classification of the planning objectives the existing literature aims to cover. Third, we provide a detailed review of demand-side modeling aspects, which includes a discussion of location methods and queuing theory. Furthermore, we analyze the literature with respect to the charging technology to be deployed, the target area of deployment, the optimization methodology and the scope of the case study. Finally, based on the previous analysis we provide a summary of the findings of this work, which allows us to discuss the current state of research and to identify several research gaps. Subsequently, we propose potential directions for future research. We conclude that the research concerning the optimal planning of CI in integrated TNs and DNS is still at an early stage. A significant part of the literature represents charging demand in a rather simplistic way and focuses on the deployment of FCI and urban areas while mostly being theoretical driven by focusing on small-scale case studies based on standard test networks. Hence, there is a need for more work in the area of the optimal planning of CI in integrated TNs and DNS. Future work should focus on more detailed modeling of charging demand that accounts for variability and uncertainty to enable a better understanding of the EV power grid impact and consider different types of charging technologies and large-scale case studies.

## Declaration of interests

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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