Delft University of Technology

CIE5050-09

Additional thesis project

Integrated fast-charging facility planning: a case study in Amsterdam

Author:
Mingjia He

Supervisor:
Panchamy Krishnakumari (TU Delft)
Ding Luo (Shell plc.)
Jiaqi Chen (Shell plc.)

Jan. 2023

Delft
University of
Technology

Abstract

With the electrification in freight transportation, fast-charging facilities are crucial to support enroute charging for long-distance freight trips. The goal of this study is to develop an integrated fast-charging facility planning framework to prepare for the increasing enroute freight charging demand in the Netherlands. Based on highway traffic data, the travel temporal and spatial patterns of general traffic flow and freight flow are extracted and analyzed comparatively. The charging demand is derived from freight traffic data, and network evaluation based on graph theory is used to identify traffic nodes with significance in highway networks. A candidate selection method is proposed to obtain potential deployment locations for charging stations and to-go chargers. On this basis, a multi-period bi-objective optimization model with minimum investment cost and maximum demand coverage is proposed to find optimal solutions for charging facility planning. The case study is formulated based on the Amsterdam highway network. The results show that the proposed model can leverage the potential of early investment to increase the final demand coverage in the last planning horizon.

1 Background

Greenhouse gases (GHGs) have posed serious threats to human living environments and ecosystems globally. According to the European Green Deal, European Commission promised significant greenhouse gas emissions reduction and a climate-neutral goal by 2050[1], which will offer substantial benefits to the environment, economy, safety, and society. Transport has become one of the major contributing sectors to emissions, accounting for approximately one-quarter of all greenhouse gas emissions in the EU[2]. Hence, the feasibility of climate stabilization goals and a decrease in GHG emissions depend on transport electrification [3]. Compared with conventional vehicles, electric vehicles (EVs) provide numerous benefits, such as producing low amounts of noise [4], being highly energy efficient and avoiding high oil prices in the future [5]. EVs also make a considerable contribution to reducing GHG emissions [3]. The Netherlands is ambitious to achieve zero-emission road traffic by 2050. Thanks to the incentivizing policy and tax-related measures, the Netherlands has become one of the leading electric transport players in the world. In 2015, the Netherlands has listed second in the global EV fleet rankings for market share, following Norway[6]. In freight transport, Netherlands' government plans to rise the market share of clean heavy-duty vehicles to reach 30%[7] by 2030. Considering the ambition of zero-emission policy and the current developing trend, the market for freight electric vehicles will grow continuously and thus requires the construction of new charging infrastructure.

There are two main types of charging solutions: alternating current (AC) slow charging and direct current (DC) fast charging. AC charging is mainly served for destination charging at workplaces or residences, as it requires more time to load. An AC slow charger may take 6–8 hours to recharge the vehicle battery to full state, while a DC fast charger can recharge up to 80% within about 30 minutes[8]. The high efficiency of DC fast chargers is attributed to the higher voltage and direct flow of DC current into the battery without conversion. This characteristic makes DC charging a promising solution for long-distance travel[8]. It allows en-route charging to ease driving anxiety and driving range restrictions. The current charging infrastructure is insufficient to support the future growth of EVs. In particular, the existing charging infrastructure lacks enough fast chargers[9]. In 2019, there are more than 200 fast-charging stations in the Netherlands. Researchers expect significant growth in the number of fast-charge points for electric cars over the coming years, to a maximum of 8,000 by 2025[10]. Amsterdam, The Hague, Rotterdam, Utrecht, and Brabantstad have been designated as the focus areas to develop charging infrastructure since 2009[6].

To promote electrification in freight transport, the goal of this research is to propose fast-charging infrastructure planning strategies for the en-route charging of commercial freight vehicles along the highway. This research builds a planning framework consisting of data fusion, network evaluation, candidate location selection, and an optimization model for planning. A multi-period bi-objective optimization model is constructed to find the optimal locations and scales of fast charging facilities considering the investment and charging-demand coverage. The research will provide evidence for long-term charging facility investment and support electrification of intercity logistics[8].

2 Literature review

With the increasing market share of electric vehicles in road transportation, extensive research has investigated the charging infrastructure-planning problem. Based on the way to represent charging demand, research approaches can be categorized into the node-based model, flow-based model, and trajectory-based model[11][12]. In the node-based model, it is assumed that the charging demand is generated at the nodes in the network[13, 14]. The flow-based model uses a set of origin–destination trips and allows charging demand to be served during journeys [15]. The trajectory-based model considers the travel pattern of electric vehicles[16, 17] and might incorporate the individual charging decision and route scheduling[18]. Optimization models would be established after obtaining charging demand. Many researchers considered multiple objectives for various benefits of different stakeholders. Yang et al.[8] established bi-objective programming models for charging demand assignment, fast charging station operation, and power line expansion, with objectives to maximize charging service profit and minimize total charging time. Bian et al.[19] proposed the charging station configuration model from the perspective of users considering traffic congestion and signal-lights waiting time. To find the Pareto optimal solution set, the simulated annealing particle swarm optimization algorithm was used with objectives of minimum investment cost, maximum profitability, and minimum time-consuming cost. Liu et at.[**?**] established the bi-level planning model for electric vehicle charging stations and used the firefly algorithm to find solutions. The upper model optimized the location and capacity of charging stations with the objective of maximizing the annual profit. The lower model optimized individual electric vehicle charging plans to achieve minimum charging cost. Wang et al.[20] proposed an optimization model for the planning of slow-charging piles and fast-charging piles, incorporating the impact of road traffic conditions on the user's charging additional cost. To efficiently find the Pareto solution sets, the NSGA-II algorithm was improved by modifying the initial population generation and crossover operator. The algorithm was proved to have better performance in terms of searchability and global convergence. Yan et al. [21] proposed a multi-objective and multivariate planning model based on hierarchical genetics considering investment costs and energy losses; compared with other algorithms, this algorithm is better for finding viable solutions in the population.

The development of charging infrastructure is likely to take several years in practice. Considering the dynamic charging demand and limited investment, it is difficult to deploy all the charging stations within one-step planning[22]. Some researchers have suggested that sing-stage optimization could lack the capacity to deal with long-term charging demand dynamics[23]. Charging infrastructure planning can be formulated as a sequential decision-making process, enabling the construction strategies to be changed according to charging demand[24, 25]. Meng el at.[26] selected candidate charging station sites based on social limitations and proposed a sequential expansion-downsizing strategy for station construction. The proposed method provided flexible construction plans to balance the increase and decrease of charging demand. The objective was to minimize the total social cost by incorporating drivers' cost and construction investment. Kadri et al.[22] used a multi-stage stochastic integer programming approach to address uncertainties in both EV-trip numbers within the road network and EV flows within trips. Scenario trees were used to approximate the evolution of the stochastic process over time, and the benders decomposition approach was extended to find optimality. Compared to the deterministic model, the proposed stochastic one provided a significantly greater coverage of charging demand. Lin et al.[12] considered the planning of large-scale charging stations for electric buses and proposed a multistage joint planning model of the transportation system and the power grid to minimize the total cost in multiple stages. Based on the assumption that the number of e-buses continues to increase, the proposed model was implemented on the Shenzhen transportation network and showed robustness to changes in demand. The research provided evidence regarding the capability of multi-stage models to transfer facility costs from later stages to early stages by considering demand in advance.

Previous studies have provided in-depth insights into the charging station location problem. A majority of charging facility deployment strategies are based solely on mathematical modeling and implemented in hypothetical scenarios. As real-world data becomes more accessible and informative, more research is needed to develop data-driven planning methods capturing valuable information from a variety of sources (traffic flow, point-of-interest (POI) information, network configuration). In addition, the charging infrastructure layout should fit in the structure of the road network, reflecting the characteristic of the network. Yet, research into potential charging station locations has rarely considered network evaluation. Furthermore, many studies have applied multi-period planning and multi-objective planning in recent years, but few have combined these two aspects into a model that takes into account both demand dynamics and benefit trade-offs. In response, the contribution of this research has three folds: 1) to leverage the information of freight traffic data and POI data into the charging facility planning process; 2) to propose a comprehensive selection process of candidate locations for charging facilities incorporating charging demand, network structure, interests of service providers, and construction flexibility; 3) to develop a multi-period bi-objective optimization model considering the charging demand dynamics over years and the trade-offs between total cost and demand coverage.

3 Methodology

3.1 Problem description

This study will model the charging facility planning problem and provide insight into how charging facility providers can make construction plans for the future of freight transportation electrification. The proposed research framework shown in Figure 1 consists of four parts: data preparation, network evaluation, candidate location selection, and charging location optimization. Data preparation and network evaluation leverage the valuable information of data and knowledge of graph theory into the planning process. Using indicators of centrality, the rankings of nodes within the highway network can be determined. We will identify the nodes that play a more significant role in the network by evaluating the connections among nodes. Moreover, a clear procedure for selecting candidate locations is established. For integrated planning, the mathematical model considered rolling-horizon optimization with two objectives minimizing total cost and maximizing demand coverage. The detailed procedures for network evaluation and candidate location selection are presented in Sections 2.3 and 2.4. A multi-period bi-objective optimization model and corresponding algorithms are illustrated in Section 2.5.

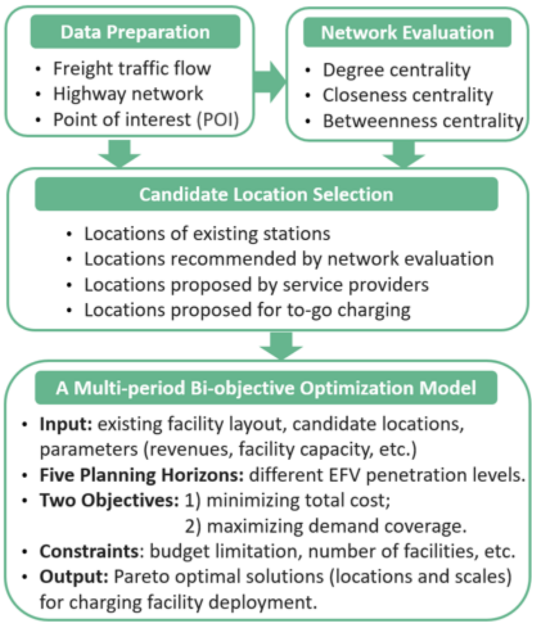


Figure 1: Research framework

3.2 Data preparation

The proposed framework will be implemented on the real highway network in the Netherlands. The datasets required in this study include freight traffic flow data, highway network data, and POI data. Traffic data on highways can be obtained from the data website, NDW[27]. We extracted one-week traffic data from the date 2022-06-27 to 2022-07-03. The traffic data includes the following information:

- Date: the date that data was collected;
- Time period: morning peak hours/ evening peak hours;
- Route ID: the ID of the route;
- Flow: the traffic flow for one segment (200 m) at a time step;
- Speed: the average speed of traffic flow for one segment in a time step;
- Vehicle class information: The flow of vehicle category includes private cars, buses, and trucks.

Freight traffic flow data can be used to determine freight charging demand. As a percentage of the total traffic flow, the market penetration rate is used to determine the amount of traffic to be charged. The datasets of the highway road network and POI data can be obtained from Open Street Map[28]. POI data would provide information on the category of locations and geographical coordinates. Figure 2 shows the highway network in the study area. In traffic flow data, roads are segmented per 200 meters. To model demand coverage, we assign the freight flow to the starting point of segments.

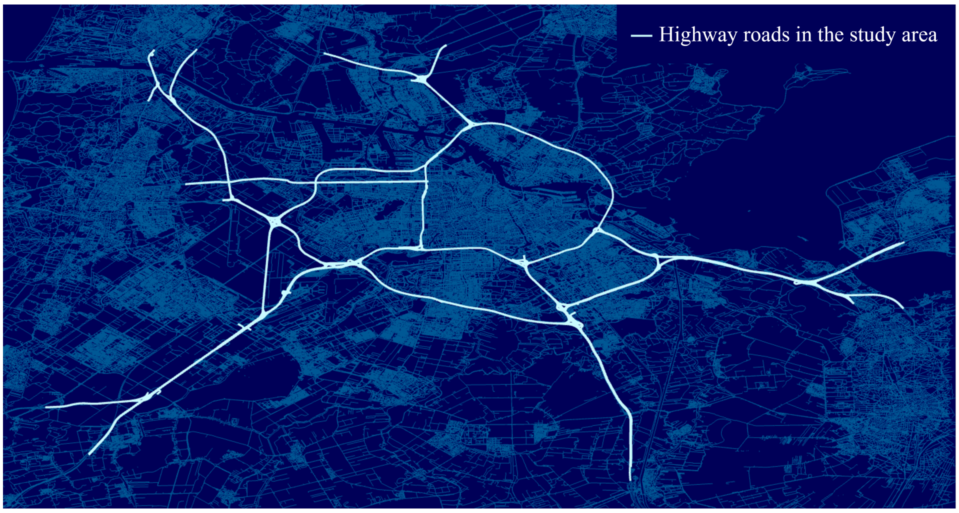


Figure 2: The study area

3.3 Network evaluation

The highway network can be defined as an undirected graph $G = (N, A)$, where N represents the set of nodes (highway junctions) and $A = \{(i, j), i, j \in N, i \neq j\}$ represents the set of arcs (roads). Network evaluation would answer the question of how important a node is in the highway network. To evaluate the role of nodes, centrality indicators are calculated including degree centrality, closeness centrality, and betweenness centrality.

Degree centrality (DC) measures the number of connected nodes. Nodes with a high degree score have higher connectiveness. DC_i is defined as follows:

$$DC_i = \frac{D}{N-1} \tag{1}$$

Where DC_i represents the number of nodes directly connected with station i; N is the total number of nodes.

Closeness centrality (CC) measures the average inverse distance to all other nodes, reflecting a node's closeness to others. Nodes with a high closeness score have a shorter total distance to all other nodes.

$$CC_i = \frac{1}{\sum_{i,j \in G, i \neq j} d_{i,j}} \tag{2}$$

Where $d_{i,j}$ represents the shortest path length between node i and node j; G is the vertices set in the network.

Betweenness centrality (BC) represents the degree to which nodes stand between each other. It involves calculating the shortest paths between all pairs of nodes in the network.

$$BC_i = \sum_{i,j,v \in G, i \neq j \neq v} \frac{\sigma_{i,j}(v)}{\sigma_{i,j}} \tag{3}$$

Where $\sigma_{i,j}$ is the total number of shortest paths from node i and node j; $\sigma_{i,j}(v)$ is the number of those paths passing through node v.

3.4 Candidate location selection

Freight transportation charges can be divided into two categories: enroute charging and destination charging. Highway charging facilities serve as enroute charging facilities. A destination charging system, on the other hand, is used at a hub or depot. Specifically, this study examines enroute charging along highways. The charging facility planning model (introduced in Section 2.4) considers deploying charging facilities in the candidate locations rather than all possible locations. There are four types of candidate locations for the deployment of charging facilities: 1) those with existing facilities; 2) those recommended by network evaluation results; 3) those selected by service providers; and 4) those for to-go charging.

Existing facilities are included first on the list as it may be more convenient to expand charging stations than build new ones. Truck parking areas are included due to the potential to be transformed into charging stations. In the second type of candidate locations, the graph theory will determine the highway nodes of importance, and candidate locations will be selected around these nodes. In Section 2.3, we described three indicators for evaluating networks: degree centrality, closeness centrality, and betweenness centrality. Furthermore, this research includes locations chosen by service providers based on business considerations. Additionally to building charging stations, fast chargers can also be deployed at supermarkets (instead of charging stations) to provide high-efficiency charging. Thus, the last type of candidate location is selected based on the supermarket along the highway.

For the selection process, POI data can be used to identify candidate locations for existing facilities and to-go charging locations. Those POIs with the labels 'fuel station', 'truck stop', and 'parking area' are considered for existing facilities, while those with the label 'supermarket' are for to-go charging. It should be noted that only POIs that are less than 500 meters from the highway are considered to serve enroute charging demand. Choosing these candidate locations involves four steps: 1) presenting POI data and road network using ArcGIS Pro; 2) selecting the stations with the required labels; 3) creating 500 m radius buffers on the road; 4) selecting the specific POIs within these buffers. Furthermore, networks are evaluated in order to determine which locations will serve important nodes.

3.5 Multi-stage bi-objective optimization model

The charging facility planning problem is formulated as an integer programming problem. A multi-stage optimization model is proposed with the objective of minimizing the total cost and maximizing the coverage number of freight vehicles. Considering the development of transport electrification, it is assumed that the proportion of electric freight vehicles is increase by the years. The notation for the optimization model is presented in Table 1.

3.5.1 Planning horizons

Five planning horizons are considered in this model representing different developing stages, each with the corresponding EFV penetration rate of 20 %, 40%, 60%, 80% and 100%. The first planning period is based on the current charging facility layout. From the second period of planning, each period will be built on the layout of previous periods, which means that the results of one horizon would offer the input of the next-horizon optimization model. The algorithm can be found in Section 2.5.4.

3.5.2 Model formulation

The first objective is to minimize the total cost in equation 4, considering that the service provider would control the project investment and reduce it as much as possible. As indicated by the previous research on charging facility planning, the total cost could be an influential factor in the scale of the planning project (e.g. number and size of charging stations). The construction cost in each horizon consists of the cost of charging stations and the cost of to-go charging at supermarkets (in Equation 5).

$$minZ_1(k) = C_k \tag{4}$$

$$C_k = \sum_{i=1}^{I} c_s^{x_i^{k-1}, x_i^k} + \sum_{j=1}^{J} (y_i^k - y_i^{k-1}) * c_t, \quad k \in K \tag{5}$$

Equation 6 shows the second objective, to maximize the coverage of charging demand. γ_k decides whether the next-horizon planning is incorporated into the current planning objectives. It is noted that when it comes to last-horizon planning, the second term will not be included by setting $\gamma_k = 0$. In Equation 7 and 8, the demand coverage is determined by electric freight flow coverage and facility capacity.

Variable	Description
Parameters	
K	Set of planning horizons.
I	Set of candidate locations for charging stations.
J	Set of candidate locations for to-go charging piles.
C_k	The total cost of the planning horizon k.
D_k	The demand coverage of the planning horizon k.
γ	The weight in the objective of demand coverage.
$c_s^{x_i^{k-1},x_i^k}$	The cost of station i from the state x_i^{k-1} to x_i^k.
c_t	The cost for installing one fast charging file near the supermarket.
d_i^k	The demand coverage of charging station i in horizon k.
d_j^k	The demand coverage of to-go charging facilities j in horizon k.
q_i^k	The freight flow can be covered by facility i.
p^k	The market penetration rate of electric freight vehicles in horizon k.
b^k	The maximum investment in horizon k.
cap_l	The capacity of a charging station with the scale l.
cap_t	The capacity of a to-go charging pile.
$Nmin^k$	The minimum number of charging stations.
$Nmax^k$	The maximum number of charging stations.
$Mmin^k$	The minimum number of locations for to-go chargers.
$Mmax^k$	The maximum number of locations for to-go chargers.
$dist_{i,j}$	The distance between station i and station j.
$dist_{min}$	The minimum distance between two charging stations.
s	The maximum construction scale of charging stations.
n	The maximum number of fast-charging plies near the supermarket.
Decision variables	
η_i^k	Binary variable: whether a charging station is deployed at the location i.
η_j^k	Binary variable: whether to-go chargers are deployed at the location j.
x_i^k	The construction scale of station i in horizon k.
y_j^k	The number of installed fast-charging piles near supermarket j.

Table 1: Variable description

The electric freight flow coverage can be calculated by penetration rate p^k multiplying the average freight flow at the nearest starting point of highway segments. Facility capacity can be determined by the construction scale of charging stations and to-go charging facilities.

$$minZ_2(k) = -(D_k + \gamma_k D_{k+1}) \tag{6}$$

$$D_k = \sum_{i=1}^{I} min(q_i^k * p^k, cap_l x_i^k) + \sum_{j=1}^{J} min(q_j^k * p^k, cap_t y_j^k), \quad i \in I, j \in J, k \in K \tag{7}$$

$$D_{k+1} = \sum_{i=1}^{I} min(q_i^k * p^{k+1}, cap_l x_i^k) + \sum_{j=1}^{J} min(q_j^k * p^{k+1}, cap_t y_j^k), \quad i \in I, j \in J, k \in K, k \neq 5 \tag{8}$$

$$\gamma_k = \begin{cases} 1 & \text{k=1,2,3,4} \\ 0 & \text{k=5} \end{cases} \tag{9}$$

Subject to constraints:

$$\sum_{i=1}^{I} c_s^{x_i^{k-1},x_i^k} + \sum_{j=1}^{J} (y_j^k - y_j^{k-1}) * c_t < b^k, \quad k \in K \tag{10}$$

$$\eta_i^k * \eta_j^k * dist_{i,j} < dist\_min, \quad i, j \in I, k \in K \tag{11}$$

$$x_i^k \leq x_i^{k+1}, \quad i \in I, k \in K \tag{12}$$

$$y_j^k \leq y_j^{k+1}, \quad j \in J, k \in K \tag{13}$$

$$Nmin^k < \sum_{i=1}^{I} \eta_i^k < Nmax^k, \quad k \in K \tag{14}$$

$$Mmin^k < \sum_{j=1}^{J} \eta_j^k < Mmax^k, \quad k \in K \tag{15}$$

$$\eta_i^k \in (0,1), \quad i \in I, k \in K \tag{16}$$

$$\eta_j^k \in (0,1), \quad j \in J, k \in K \tag{17}$$

$$0 \leq x_i^k \leq s, \quad i \in I, k \in K \tag{18}$$

$$0 \leq y_j^k \leq n, \quad j \in J, k \in K \tag{19}$$

The limitations for investment are set for each planning horizon. The constraint in (10) ensures that the cost in each horizon can not exceed the pre-set value. The constraint in (11) indicates that the distance between two stations should be larger than the minimum distance threshold. The constraints in (12) and (13) ensure that the scale of charging stations and the number of to-go chargers can not decrease with development, as it is considered that the charging facilities constructed in the previous horizons will remain in the subsequent horizons. For the first horizon ($k = 1$), the planning is based on the initial (existing) facility layout ($k = 0$). The constraints in (14) and (15) set the restrictions on the number of facilities. The constraint in (16) and (17) represent the binary decision variables on whether to build facilities on candidate locations. The constraint in (18,19) defines two sets of integer variables for the scale of charging facilities, namely, scales of charging stations xx_i^k and scales of to-go charging facilities y_i^k.

3.5.3 Solution algorithm

The non-dominated sorting genetic algorithm II (NSGA-II) has been widely used for solving multi-objective optimization problems, especially bi-objective function optimization problems, due to its robustness and ability to find Pareto optimal solution. This research applied the classical NSGA-II to solve the bi-objective optimization problem with multiple horizons. The optimization process of NSGA-II is as follows: 1) The first step is to randomly generate the initial population based on the problem range and constraint; 2) the objective values are calculated based on the generated population. 3) Based on the non-dominated theory of the population, members are assigned a non-dominated solution, and solutions are stored in each level of the Pareto set; 4) Once the sorting is complete, the crowding distance is calculated. In the selection, the crowding comparison operator is used to sort the solutions in the Pareto set. Those solutions with a low rank and large crowding distance will be selected for the next generation; 5) By mutation and crossover mating of selected parents, the new offspring is generated. The new offspring and the parent population are then merged to create a combined population; 6) The procedure will stop and output the Pareto front until the maximum number of iterations is reached. For more detailed information about this algorithm, we recommend the research of [29].

Figure 3 shows how NSGA-II can be used to solve the proposed multi-stage bi-objective optimization model. In each planning horizon, NSGA-II will be used to produce Pareto optimal solutions. These solutions will be compared to select one for implementation and to be used to update the facility layout preparing for the next-period optimization.

4 Numerical experiments

4.1 Travel pattern analysis

Figure 4 (a)-(d) shows the traffic flow on workdays and weekends during morning peak hours (MPH) and evening peak hours (EPH). By comparing Figure 4 (a)(b) to Figure 4 (c)(d), it can be seen that the overall traffic demand on workdays was higher than that on weekends considering both morning peak and evening peak. During the morning peak hours on workdays, more demand occurred in the north part

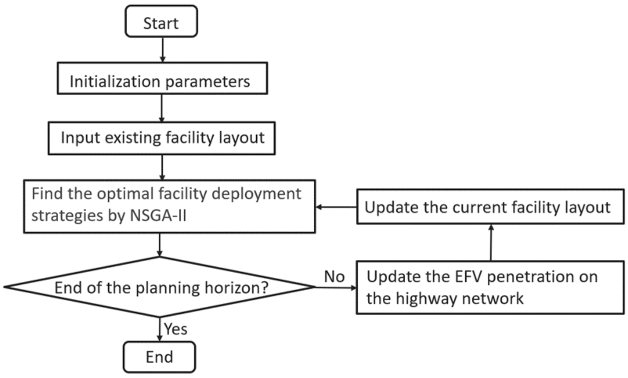


Figure 3: The procedure of optimization

of the study area, such as A4, A9, and A2. In the evening, the demand became lower especially in the north while A9 and A1 still had heavy traffic demand. On weekends (Figure 4 (c)), the traffic demand of the road network maintained at a low level with an average volume below 1400 vehicles per hour in the morning. While during the evening peak hours, more vehicles used A9, A4, and A1.

The temporal and spatial distributions of truck demand (in Figure 5 (a)-(d)) were relatively different from the overall traffic on the highway. Temporal patterns of truck volume were similar between workdays and weekends, morning and evening. When looking into the spatial distribution, it can be found that the truck travel demand on some road segments stayed significantly high on both workdays and weekends, including A9, the intersection of A1 and A10, southwest part of A10. The segments of A4 and A1 in suburban areas had high traffic demand, however, the average truck demand remained below 25 vehicles per hour.

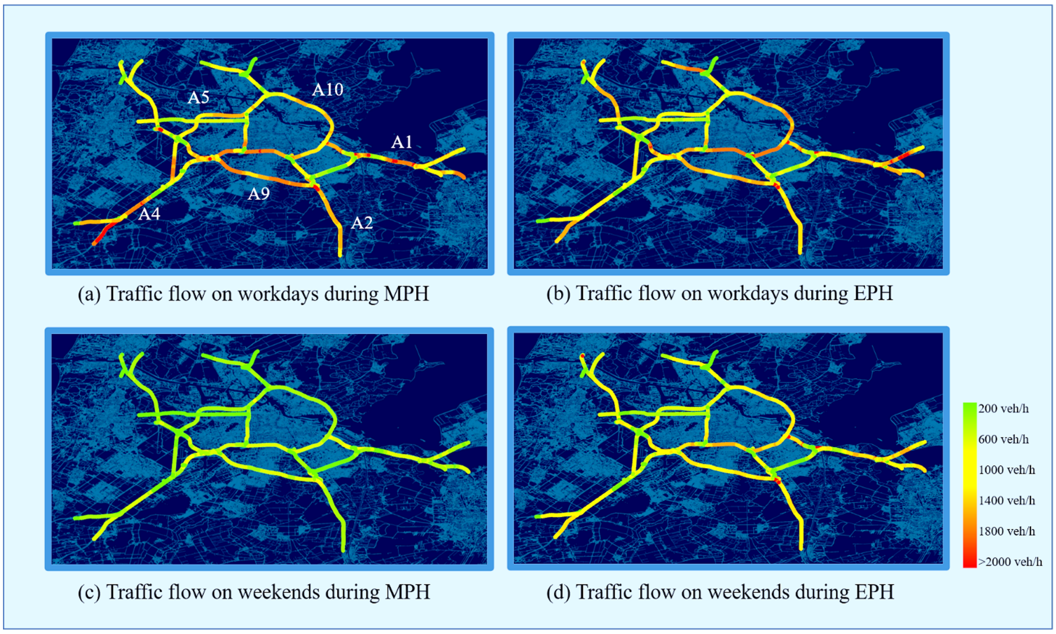


Figure 4: The distribution of overall traffic flow

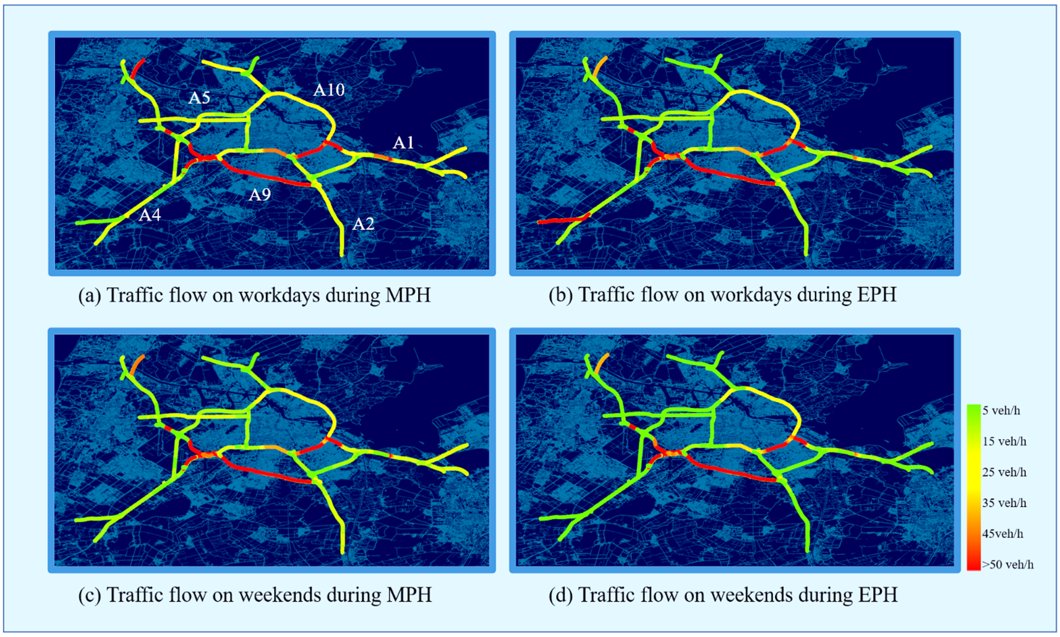


Figure 5: The distribution of truck traffic flow

4.2 Candidate location selection

To select the candidate locations, POI information was filtered according to the built-environment category. POIs with the label 'fuel station', 'parking area', 'truck stop', and 'supermarket' remained. It is noted that only the locations that lie in the 500-meter buffering of the highway would be used as candidates. Next, nodes in the highway network were evaluated. Table 2 shows the numerical evaluation results. The indicators, degree centrality (DC), closeness centrality (CC), and betweenness centrality (BC) were calculated and normalized. The score was the average of indicators. Node 17 ranked the top with the highest values for all indicators, followed by Node 11, 5, and 3.

Rank	Score	DD	BC	CC	ID	Rank	Score	DD	BC	CC	ID
1	1.673	1.000	0.363	0.310	17	17	0.983	0.667	0.127	0.189	13
2	1.609	1.000	0.342	0.267	11	18	0.879	0.667	0.000	0.212	32
3	1.489	1.000	0.202	0.287	5	19	0.846	0.667	0.000	0.179	1
4	1.446	1.000	0.181	0.265	3	20	0.705	0.333	0.085	0.287	6
5	1.250	0.667	0.306	0.277	20	21	0.655	0.333	0.065	0.256	10
6	1.209	0.667	0.249	0.292	18	22	0.389	0.000	0.181	0.208	26
7	1.188	0.667	0.226	0.295	4	23	0.304	0.000	0.127	0.177	28
8	1.164	0.667	0.249	0.248	25	24	0.209	0.000	0.000	0.209	31
9	1.136	0.667	0.202	0.267	24	25	0.185	0.000	0.000	0.185	16
10	1.130	0.667	0.239	0.225	12	26	0.185	0.000	0.000	0.185	22
11	1.095	0.667	0.166	0.263	9	27	0.185	0.000	0.000	0.185	23
12	1.056	0.667	0.137	0.252	8	28	0.179	0.000	0.000	0.179	0
13	1.018	0.667	0.127	0.225	21	29	0.160	0.000	0.000	0.160	14
14	1.010	0.667	0.127	0.217	2	30	0.160	0.000	0.000	0.160	15
15	1.007	0.667	0.069	0.272	7	31	0.151	0.000	0.000	0.151	29
16	1.003	0.667	0.055	0.282	19	32	0.151	0.000	0.000	0.151	30

Table 2: The numerical results of network evaluation

Figure 6 shows the distribution of nodes in the highway network. The nodes in red color represented the nodes with the top 10 rankings, which play a more important role in this highway network. These nodes were the highway junctions that were more connected with other junctions and were more likely to influence other junctions in the network. As shown in Figure 7, 119 candidate locations are selected in total, with 84 candidates for charging station deployment and 35 candidates for to-go charging points installment. The candidates selected by POI data accounted for the largest proportion 63.4%. According to the network evaluation, 15 candidate locations were added near the top 10 nodes in the network, as indicated by the orange points.

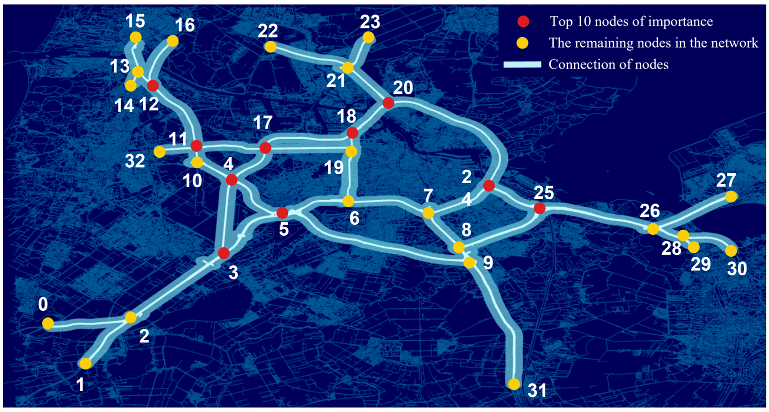


Figure 6: The distribution of evaluated nodes

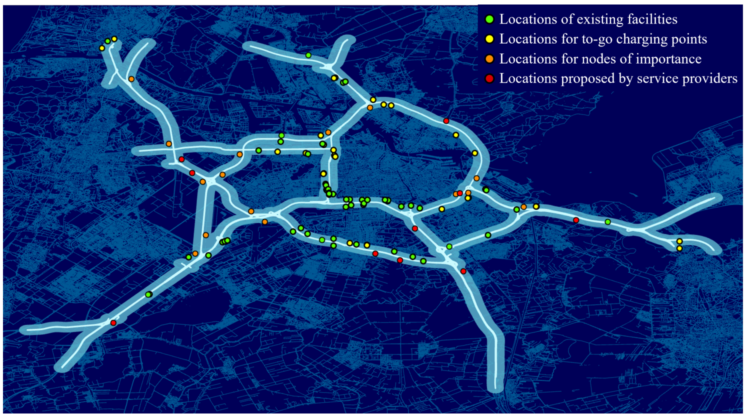


Figure 7: The distribution of evaluated nodes and candidate locations

4.3 Integrated charging facility planning

The optimization model can find the (near) optimal solutions for locations and construction scales of charging facilities. For charging stations, we define five construction scales for charging stations, extremely-small scale stations, small-scale stations, medium-scale stations, large-scale stations, and extremely-large-scale stations, represented by $x_i^k = (1, 2, 3, 4, 5)$. $x_i^k = 0$ means there is no station constructed at the location i. For to-go chargers at supermarkets, we optimize the number of charging piles to install (y_i^k). The optimization model has parameters in terms of investment, capacity, construction scale, distance, etc. The settings of parameters are presented in Table 4 in Appendix A. In setting these parameters, we have taken into account the parameter settings in previous research [3, 30] and have tuned the parameters based on our case study. For NSGA-II algorithm, we set the population size to be 500, the iterations number to be 300, the crossover probability to be 0.9, and the mutation probability to be 0.1.

4.4 Results of multi-period facility planning

During multistage planning, the initial results of the infrastructure planning can certainly affect subsequent planning stages. As bi-objective optimization could have more than one optimal solution in each horizon, called Pareto optimal solutions, one solution should be selected from the Pareto set for the next-horizon planning. To evaluate these impacts of solution selection, two scenarios are defined following different solution selection rules in each horizon planning. In Scenario 1, the solution with maximum demand coverage was selected for next-horizon planning. In Scenario 2, the solution with (the nearest) median demand coverage was selected. To evaluate the performance of looking ahead policy of our model, we defined Scenario 3 in which the planning of each horizon only considers the demand in the current horizon, instead of the potential changing in the nearest future. In Scenario 3, the objective on the demand coverage only considers the effects on the current horizon, and the solution with maximum demand coverage was selected for next-horizon planning.

By comparing Scenario 1 and Scenario 2, we can observe the impact of solution selection on the final deployment layout. And Scenario 2 and Scenario 3 can show whether planning one step ahead can benefit long-term planning. As shown in Table 3, Scenario 1 has a total cost of 6.250 million euros (MER), and the demand coverage can reach 369 freight vehicles per hour in the last planning horizon. Scenario 2 saves 61% of total cost compared to Scenario 1, the covered demand decreases by 29%. Therefore, selecting maximum demand coverage in every horizon could obtain solutions with higher demand coverage, while it is noted that the cost-efficiency of investment could be smaller. When looking into the planning horizons, it could be found that Scenario 1 tends to construct new facilities as many as possible reaching the upper limit of the maximum number of facilities. The investigation of to-go chargers at the early stage indicates the advantage of flexible chargers at supermarkets for capturing charging demand with a relatively lower initial investment. The number of facilities in Scenario 2 is above the half level of that in Scenario 1.

Compared to Scenario 1, Scenario 3 neglects the growth of charging demand and tends to invest less in the first four horizons. Although in each horizon, Scenario 3 selects the solution with the largest demand coverage, it covers 94% charging demand compared to that in Scenario 1. In the final horizon, Scenario 1 constructed more charging stations than Scenario 3 and have the same number of to-go chargers.

	Horizon 1	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Total
Scenario 1						
Construction cost (MEUR)	1.450	1.500	1.000	1.300	1.000	6.250(100%)
Demand coverage (veh/h)	98	204	256	316	369	369(100%)
Number of stations	9	12	12	13	15	15
Number of to-go chargers	25	25	25	25	25	25
Scenario 2						
Construction cost (MEUR)	0.03	0.508	0.508	0.502	0.9	2.448(39%)
Demand coverage (veh/h)	37	95	157	203	262	262(71%)
Number of stations	7	8	9	10	11	11
Number of to-go chargers	15	19	23	24	24	24
Scenario 3						
Construction cost (MEUR)	1.142	1.458	0.700	0.950	1.100	5.350(86%)
Demand coverage (veh/h)	98	196	256	304	346	346(94%)
Number of stations	9	11	12	12	12	12
Number of to-go chargers	21	25	25	25	25	25

Table 3: The optimization results of Scenario 1, Scenario 2, and Scenario 3

Figure 8 showed the distribution of charging facility deployment plans of Scenario 1 and Scenario 2 respectively. In order to display the locations of newly constructed stations, existing stations are not shown. The yellow points represent the constructed charging stations only in Scenario 1. The red points represent the charging stations constructed both in Scenario 1 and Scenario 2. It should be noted that the locations for charging stations in Scenario 2 are also selected in Scenario 1. The overlap of scenarios may help facility planners to identify the locations that are more cost-efficient in the configuration of optimal deployment strategies. The spatial distribution of these stations is in line with the highway segments with high freight traffic flow in 5.

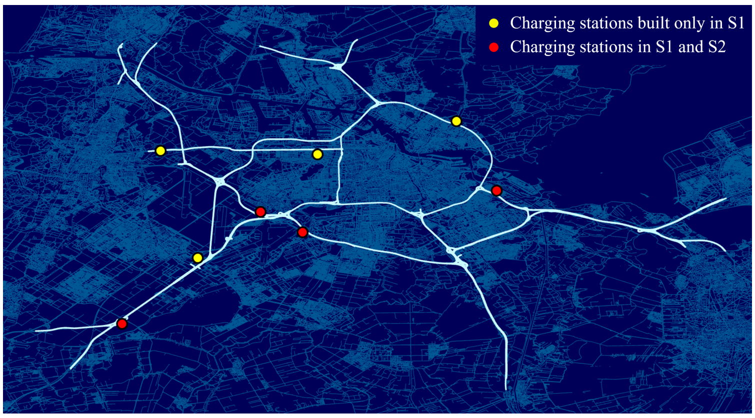
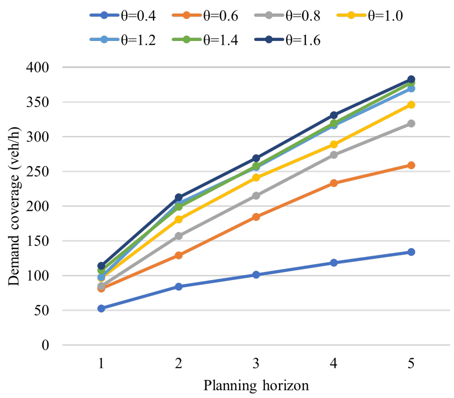


Figure 8: The distribution of charging stations in Scenario 1 and Scenario 2

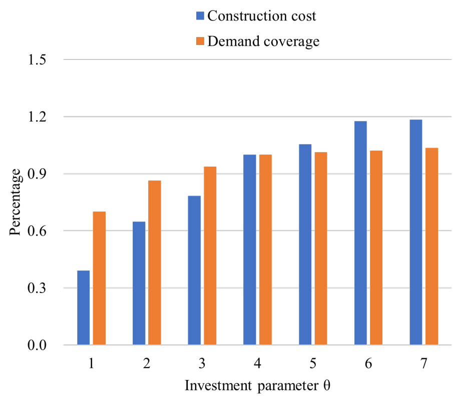
4.5 Sensitivity analysis on investment limitation

In the optimization model, the cost in each horizon can not exceed an investment limit ($b = 1.5$ million euro). To investigate the impact of the investment limitation, we defined an investment rate θ. By setting the maximum investment to be $b * \theta$, the optimization results for $\theta = 0.4$, 0.6, 0.8, 1.0, 1.2, 1.4, and 1.6 in each horizon were derived and the demand coverages were presented in Figure 9a. The demand coverage grows with facilities building/upgrading from Horizon 1 to 5. Higher values of investment limits result in larger demand coverage in each horizon. The investment limitation has a significant impact on increasing demand coverage when θ increases from 0.4 to 1.0. It is possible that θ =1.4 may leverage the full potential of investment, as the small difference between θ =1.4 and θ =1.6 may result from limitations on facility size and number. In addition, the market penetration rate of freight vehicles has been set to be increased evenly across horizons, the covered demand does not change in the same manner. With the larger value of θ, the slopes of lines in Figure 9a become closer to the growth rate of market penetration.

Taking $\theta = 1.0$ as the reference, Figure 9b shows the percentages of total construction cost and demand coverage with varying θ. It is noted that θ less 1.0 could produce solutions that are more cost-efficient, as the percentage of total construction cost is lower than the percentage of demand coverage. Therefore, higher investment limitation tends to increase charging demand coverage, but this effect weakens as it increases. When θ is larger than 1.0, even with higher investment, the demand coverage can not be improved significantly.



(a) The demand coverage in each planning horizon



(b) The total demand coverage of planning horizons

Figure 9: Sensitivity analysis of investment limitation

5 Conclusion

To prepare for the increasing enroute freight charging demand in the Netherlands, this study aims to develop an integrated fast-charging facility planning framework. Using highway traffic data, the temporal and spatial patterns of general traffic flow and freight flow are extracted and compared. We derive charging demand based on freight traffic data and use graph theory to identify significant traffic nodes along highways. To locate potential deployment sites for charging stations and to-go chargers, a method of candidate selection is proposed. We propose a multi-period bi-objective optimization model to find optimal charging facility locations with minimum investment cost and maximum demand coverage. Based on the network of highways in Amsterdam, a case study is developed and NSGA-II is implemented to solve the model. In scenario comparison, the scenario (Scenario 1) that considers next-horizon planning and selects the solution with highest demand coverage can cover larger number of charging demand than other scenarios (Scenario 2 and 3). In sensitivity analysis, it is found that when the parameter θ is less than 1.0, higher investment can significantly increase demand coverage in each horizon, and the impact decreases as the investiment increases.

In the future, the research framework can include logistics-related POI information including distribution centers, warehouses and use the origin-destination data of electric freight vehicles. In addition, this research applis Euclidean distance to select the potential locations, however, this can be less realistic as roads in the real-world network are connected. Future research may consider obtain the route between potential stations and freight vehicles on highways and calculate the charging demand coverage based on the real network. It is assumed in this study that the market penetration rate will increase evenly over time and the value will be the same for each road segment. Future study may predict the specific number of electric freight vehicles and identify the charging demand according to the journey of vehicles and state of charge. Finally, this study take the highway near Amsterdam as a case study, more investigations can be done to extend the problem modeling to large highway networks.

References

[1] European Commission. A european green deal. https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal$_en, 2019(accessed2023)$.

[2] European Environment Agency. Share of transport greenhouse gas emissions. https://www.eea.europa.eu/data-and-maps/daviz/share-of-transport-ghg-emissions-2tab%02googlechartid$_chart_13, 2019(accessed2023)$.

[3] Jiale Li, Zhenbo Liu, and Xuefei Wang. Public charging station location determination for electric ride-hailing vehicles based on an improved genetic algorithm. *Sustainable Cities and Society*, 74:103181, 11 2021.

[4] Hector Campello-Vicente, Ramon Peral-Orts, Nuria Campillo-Davo, and Emilio Velasco-Sanchez. The effect of electric vehicles on urban noise maps. *Applied Acoustics*, 116, 2017.

[5] Yanchong Zheng, Ziyun Shao, Yumeng Zhang, and Linni Jian. A systematic methodology for mid-and-long term electric vehicle charging load forecasting: The case study of shenzhen, china. *Sustainable Cities and Society*, 56, 2020.

[6] Netherlands Enterprise Agency. Misson Zero Powered Netherlands. Technical report, 2019.

[7] The Government of Netherlands. Glasgow climate summit: agreement on more clean heavy-duty vehicles. https://www.government.nl/latest/news/2021/11/10/glasgow-climate-summit-agreement-on-more-clean-heavy-duty-vehicles, 2021 (accessed 2023).

[8] Dingtong Yang, Navjyoth J.S. Sarma, Michael F. Hyland, and R. Jayakrishnan. Dynamic modeling and real-time management of a system of EV fast-charging stations. *Transportation Research Part C: Emerging Technologies*, 128(April):103186, 2021.

[9] Fangzhou Xia, Hongkun Chen, Hao Li, and Lei Chen. Optimal planning of photovoltaic-storage fast charging station considering electric vehicle charging demand response. *Energy Reports*, 8:399–412, 2022.

[10] Netherlands Enterprise Agency. Vision on the charging infrastructure for electric transport. Technical report, 2017.

[11] Mouna Kchaou-Boujelben. Charging station location problem: A comprehensive review on models and solution approaches. *Transportation Research Part C: Emerging Technologies*, 132:103376, 2021.

[12] Yuping Lin, Kai Zhang, Zuo Jun Max Shen, Bin Ye, and Lixin Miao. Multistage large-scale charging station planning for electric buses considering transportation network and power grid. *Transportation Research Part C: Emerging Technologies*, 107:423–443, 10 2019.

[13] Sylvia Y. He, Yong Hong Kuo, and Dan Wu. Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: A case study of beijing, china. *Transportation Research Part C: Emerging Technologies*, 67:131–148, 6 2016.

[14] Jaeyoung Jung, Joseph Y.J. Chow, R. Jayakrishnan, and Ji Young Park. Stochastic dynamic itinerary interception refueling location problem with queue delay for electric taxi charging stations. *Transportation Research Part C: Emerging Technologies*, 40:123–142, 3 2014.

[15] Fei Wu and Ramteen Sioshansi. A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows. *Transportation Research Part D: Transport and Environment*, 53:354–376, 6 2017.

[16] Jie Yang, Jing Dong, and Liang Hu. A data-driven optimization-based approach for siting and sizing of electric taxi charging stations. *Transportation Research Part C: Emerging Technologies*, 77:462–477, 4 2017.

[17] Wei Tu, Qingquan Li, Zhixiang Fang, Shih lung Shaw, Baoding Zhou, and Xiaomeng Chang. Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach. *Transportation Research Part C: Emerging Technologies*, 65:172–189, 4 2016.

[18] Qi Liu, Jiahao Liu, Weiwei Le, Zhaoxia Guo, and Zhenggang He. Data-driven intelligent location of public charging stations for electric vehicles. *Journal of Cleaner Production*, 232:531–541, 9 2019.

[19] Haihong Bian, Chengang Zhou, Zhengyang Guo, Ximeng Wang, Ying He, and Shan Peng. Planning of electric vehicle fast-charging station based on poi interest point division, functional area, and multiple temporal and spatial characteristics. *Energy Reports*, 8:831–840, 11 2022.

[20] Limeng Wang, Chao Yang, Yi Zhang, and Fanjin Bu. Research on multi-objective planning of electric vehicle charging stations considering the condition of urban traffic network. *Energy Reports*, 8:11825–11839, 11 2022.

[21] Xiangwu Yan, Cong Duan, Xiao Chen, and Zhengyang Duan. Planning of electric vehicle charging station based on hierarchic genetic algorithm. 2014.

[22] Ahmed Abdelmoumene Kadri, Romain Perrouault, Mouna Kchaou Boujelben, and Céline Gicquel. A multi-stage stochastic integer programming approach for locating electric vehicle charging stations. *Computers Operations Research*, 117:104888, 5 2020.

[23] Meng Li, Peng Tang, Xi Lin, and Fang He. Multistage planning of electric transit charging facilities under build-operate-transfer model. *Transportation Research Part D: Transport and Environment*, 102:103118, 2022.

[24] Hasan Mehrjerdi. Dynamic and multi-stage capacity expansion planning in microgrid integrated with electric vehicle charging station. *Journal of Energy Storage*, 29:101351, 6 2020.

[25] Shakti Vashisth, Praveen Kumar Agrawal, Nikhil Gupta, K. R. Niazi, and Anil Swarnkar. Multistage planning of fast charging stations for pevs using traffic-based approach. *Sustainable Energy, Grids and Networks*, 30:100662, 6 2022.

[26] Xuyao Meng, Weige Zhang, Yan Bao, Yian Yan, Ruiming Yuan, Zhen Chen, and Jing Xin Li. Sequential construction planning of electric taxi charging stations considering the development of charging demand. *Journal of Cleaner Production*, 259:120794, 6 2020.

[27] Nationaal Dataportaal Wegverkeer. Highway data. https://www.ndw.nu/, 2022 (accessed 2023).

[28] OpenStreetMap. Open street map. https://www.openstreetmap.org, 2022 (accessed 2023).

[29] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002.

[30] Xiaomei Wu, Qijin Feng, Chenchen Bai, Chun Sing Lai, Youwei Jia, and Loi Lei Lai. A novel fast-charging stations locational planning model for electric bus transit system. *Energy*, 224:120106, 6 2021.

6 Appendix

6.1 Appendix A

The parameters are listed in Table 4. The values of station capacity and construction cost are related to the construction scale. The parameters for investment limits, market penetration rate, and the number of facilities are related to the planning horizons. In setting these parameters, we have taken into account the parameter settings in previous research [3, 30] and have tuned the parameters based on our case study.

Variable	Setting
dist_{min}	3 (km)
s	5
n	5
c_t	2000 (euro)
$\text{cap}_l, l \in L$	[0, 30, 35, 40, 45, 50] (vehicles/hour)
cap_t	2 (vehicles/hour)
$\text{p}^k, k \in K$	[0.2, 0.4, 0.6, 0.8, 1]
$\text{b}^k, k \in K$	[1.5, 1.5, 1.5, 1.5, 1.5, 1.5] (million euro)
$\text{Nmin}^k, k \in K$	[0, 0, 0, 0, 0]
$\text{Nmax}^k, k \in K$	[5, 5, 5, 5, 5]
$\text{Mmin}^k, k \in K$	[0, 0, 0, 0, 0]
$\text{Mmax}^k, k \in K$	[15, 15, 15, 15, 15]
$\text{c}_s^{0,l}, l \in L$	[[0, 0.5, 0.6, 0.7, 0.8, 0.9] (million euro)
$\text{c}_s^{1,l}, l \in L$	[0, 0, 0.2, 0.3, 0.4, 0.5] (million euro)
$\text{c}_s^{2,l}, l \in L$	[0, 0, 0, 0.25, 0.35, 0.45] (million euro)
$\text{c}_s^{3,l}, l \in L$	[0, 0, 0, 0, 0.3,0.4] (million euro)
$\text{c}_s^{4,l}, l \in L$	[0, 0, 0, 0, 0, 0.45] (million euro)

Table 4: Parameter settings