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Three-step procedure for locating and sizing electric vehicle charging stations

Case study of the city of Brussels

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Contents

Abstract

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Recently, a great deal of research has been conducted on the optimal location and size of electric vehicle charging stations to help build a charging infrastructure that can address one of the biggest challenges of the environmental transition: mobility.
In studying the problem of the optimal location and size of electric vehicle charging stations, three main perspectives can be taken: that of the charging station owners, that of the electric vehicle users, and that of the electricity distribution network, each with specific objectives. This thesis aims to describe a three-step procedure addressing the location and sizing problem, taking into account the perspectives of the various stakeholders. Eventually this procedure will be applied to the practical case of the Brussels-Capital Region. The first step consists in the probabilistic evaluation of candidate sites based on qualitative criteria. The second step approximates the optimal solution through a heuristic. Thereafter, the mathematical optimization problem is defined and solved for exact solutions with different parameter. Finally, results of the various steps are compared, conclusions and future areas of improvement are identified.

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List of abbreviations

CS	Charging Stations
CSO	Charging Station Owners
DN	Distribution Network
EV	Electric Vehicles
EVCS	Electric Vehicles Charging Stations

Chapter 1

Introduction

In 2020, road transport alone was responsible for about 20% of total CO_2 emissions in Belgium (EDGAR - The Emissions Database for Global Atmospheric Research, 2022). These figures can be generalized to all industrialized countries, in some of which the share of transport is even higher. There is no doubt that mobility is a major concern within the general issue of ecological transition. One of the solutions often envisaged is the development of the electric mobility market. In line with this growing concern, the European Union is promoting initiatives aimed at developing networks for electric cars across the continent, such as projects to mandate the installation of electric charging stations every 60 km by 2026[1].

However, many elements are still considered barriers to adoption by a large proportion of potential users. Among them, two main elements: the price of an electric vehicle (which is on average higher than that of a vehicle with an internal combustion engine) and the inconvenience often associated with charging these electric vehicles (Coffman et al., 2017). Indeed, in order for electric mobility to become a credible alternative to thermal vehicles, it is necessary to deploy reliable, accessible and efficient charging infrastructures. Therefore, the problem of locating charging stations has become increasingly important. The search for optimal placements aims at enabling demand coverage, efficient use of resources and improved user comfort. However, optimizing of charging station location is still a fairly recent problem, with the first literature dating back to 2011 with Frade et al., seeking to find the optimal locations for the charging stations for the Avenidas Romas neighborhood, Lisbon. Since then, the problem has been widely studied in the academic world to develop this critical aspect of the electric vehicle market.

Several approaches and perspectives can be considered for this localization problem. In summary, there are three main perspectives. First, there is the electrical distribution network perspective. The main objective of site optimization from this perspective is to select the sites that minimize the total load of the stations to be installed. This perspective has been widely studied in the literature since Rahman et al. (2013). Secondly, there is the perspective of charging station owners. Here, the goal is to find locations that minimize costs for the owners. The first to study this perspective were Xi et al. (2013). Finally, the third perspective is that of electric vehicles users who want to maximize their comfort (Moradijoz et al., 2013). However, studies combining several papers soon appeared (Pazouki et al., 2013), as it was felt that considering only one of the three approaches would be too restrictive.

[1]For more details on the European vision for CO_2 emissions from the transport sector, see the following report, "European Green Deal: Commission proposes transformation of EU economy and society to meet climate ambitions."

Today, there are as many modelling approaches to the problem as there are case studies that have been conducted. Indeed, the perspectives considered, the proposed model and the procedure depend directly on the concerned geographical area . For example, less common procedures have emerged with the evaluation of candidate locations through a Bayesian Network (BN) as done by Hosseini and Sarder, 2019 or Deb et al., 2019.

The Brussels-Capital Region has long been aware of the important role that cities have to play in the fight against global warming. Back in 2017, the Region began implementing its first decarbonization measures by defining a clear long-term vision for Brussels' vehicle fleet in 2025. Since then, many initiatives have been launched. Among them is the "strategic vision for the development of charging infrastructure", which has been be approved by the government in June 2020. This is an ambitious plan that aims to increase the number of charging stations in the Brussels-Capital Region. The goals of this plan are many. They include the creation of a charging network accessible to all users of electric vehicles, the promotion of their use, and the implementation of measures to encourage the use of these "green" means of transport.

In order to achieve these objectives, the deployment strategy is organized around several specific actions. Obviously, the main one consists of the installation of numerous recharging stations in the Brussels-Capital Region. This installation will take place on public parking spaces, in public parking lots, in petrol stations, in residential buildings or in public buildings. In the end, the strategy aims at a deployment such that there would be one charger for every 10 electric cars in the region.

Several initiatives are aimed at encouraging the installation of charging stations by building owners. The region offers some subsidies or grants for the installation of new charging stations. The strategy also includes training programs for electricians and installers of charging stations to ensure the quality and safety of installations.

In addition to the installation of charging stations, the Brussels-Capital Region is also planning measures to promote the use of these less polluting vehicles (electric and plug-in hybrids). This includes, among other things, the promotion of awareness programs for the region's residents and for the companies operating in the region, promotional marketing campaigns to highlight the benefits of these alternatives, the expansion of EV fleets for public services and financial incentives such as purchase subsidies or tax and parking fee exemptions. In addition, the strategy encourages employers to offer EV-related benefits (such as reimbursement programs).

In conclusion, the strategy for the deployment of charging infrastructure in the Brussels-Capital Region is a long-term and ambitious plan that aims to foster the adoption of electric (or plug-in hybrid) means of locomotion by the region's inhabitants. By providing a charging infrastructure that is sufficient to meet demand, efficient and easily accessible. The region will encourage the use of these modes of transportation. To achieve this, the strategy calls for the creation of a charging network, its promotion and the implementation of various benefits.

Furthermore, one of the challenges of deployment is the pace at which it occurs. Deployment that is too fast would create inefficiencies of several kinds: too fast and too large investments, too important burden on the electrical distribution network, and above all, pressure on parking for non-electric vehicles. On the contrary, a too slow deployment would result in a failure to meet the charging demand.

This deployment strategy is an example of the involvement of public authorities in the fight against global warming. By promoting the use of these more sustainable modes of transport, the Brussels-Capital Region hopes to reduce its greenhouse gas emissions and improve air quality in the region.

This thesis is at the crossroad of both matters, namely, the problem of optimally locating charging stations and the challenges faced by the city of Brussels. Therefore, it provides decision makers with a clear procedure to tackle the problem of locating and sizing charging infrastructures in Brussels. Two important things must be emphasized in this respect. First, the city of Brussels has already started installing charging stations on its territory[2]. These charging points are mostly built by private actors and won't be considered in the optimization problem due to unavailability of recent private data. Secondly, we describe an implementation procedure taking a global public perspective in which the 19 municipalities of Brussels do not take individual decisions.

Chapter 2 provides a literature review in order to analyze the techniques and approaches that have already been developed and modeled in the literature. Thereafter, Chapter 3, proposes modeling procedures appropriate for the case of the city of Brussels, namely a three-step procedure to evaluate candidate locations for electric vehicles charging. The first step is a probabilistic evaluation based on a probabilistic network, the second is an approximation to the optimal solution based on a greedy heuristic, and the third consists of the resolution of the formal optimization model using a solver (in our case it will be Gurobi via the Pyhton interface). Eventually, Chapter 4 describes the necessary data for the implementation of these techniques and models in order to obtain the results that are presented in the Chapter 5.

Gurobi Gurobi is a commercial software suite designed to solve linear optimization problems. In practice, Gurobi is widely used. This is especially the case in academia because of its efficiency, its high solving capacity and its advanced features. In our case we decided to use it for its widely accessible documentation and performance in solving linear optimization problems.

[2]An overview of existing charge points can be found in: "Delivery Plan: stratégie de déploiement de l'infrastructure de la recharge dans la région Bruxelles-Capitale.".

Chapter 2

Literature Review

In recent years, research on the optimal location for electric vehicles (EV) has proliferated to address one of the biggest challenges of the environmental transition: mobility.

The issue of electric vehicles is an advanced technological issue. It is not just about understanding that vehicles run on electricity. It is also about understanding how this is done in practice, the sources of electricity, the advantages and disadvantages of this technology, and the future of mobility. An overview of these elements is provided by Ahmadi et al. (2016) and Narasipuram and Mopidevi (2021). From these publications, it is clear that the problem of the optimal location of charging stations is still one of the factors considered as a major disadvantage of electric vehicles compared to thermal vehicles.

When it comes to optimizing the location and sizing of electric vehicle charging stations, researchers can take, in short, three main approaches to address the problem. Each of them is accompanied by specific objective functions and constraints (Ahmad et al., 2022). The first examines the perspective of the charging station owners (CSO), the second addresses the distribution networks (DN) responsible for supplying electricity to a given commercial, residential, or industrial area, and the last one examines the perspective of electric vehicles (EV) users. Combinations of these different approaches will also be analyzed.

This chapter is dedicated to the review of the literature. Thus, each section is dedicated to one of the commonly used approaches when it comes to optimal placement and optimal sizing of charging stations (CS). The following sections are organized according to the approach they take and thus the objective functions they consider.

2.1 Charging Station Owner's Perspective

The goal of owners is to get the maximum benefit from the operation of their charging stations. Therefore, CSO look for locations for implementing charging stations that minimize the associated costs or that maximize the revenue of these charging stations.

From the CSO perspective, the associated costs are significant (Smith and Castellano, 2015). For this reason, the literature has quickly begun to consider these costs as an objective function.

The first authors to examine these costs were Lam et al. (2014), who addressed the problem by examining the optimal locations for building new charging stations. They considered that the use of gas stations for the implementation of CS (charging station) would not be optimal because these stations are intended for combustion-powered vehicles and EV would take up too much available space. Therefore, they optimized the location of the new charging stations to minimize construction costs. Of the constraints inserted into the model, all were included to ensure mathematical consistency of the problem, but none of them truly represent the behavior of the existing network, such as some constraints that represent the behavior of users when faced with a charging need (i.e., go to the nearest station, charge only when needed, etc.). In fact, their focus was on the supply side of the charging facility (CSO) rather than the demand side (the users). Later, constraints representing user behavior were added to the model to obtain more consistent results in real implementation contexts (without putting users at the center of the objective function).

Faridpak et al. (2019) also addressed the problem of the optimal CS location problem considering an objective function related to cost. In this case, they proposed to minimize the total cost (not only the construction cost) of Electric Vehicles Charging Stations (EVCS). To obtain a more accurate estimate of the marginal cost associated with demand, they modeled the schedule of charging cycles as well as the charging time interval by a Gaussian PDF (probability density function), assuming a stochastic charging pattern in the behavior of EV users. The first step in their solution process is to determine the location of minimum cost EVCS capable of meeting EV charging demand. This first step leads to optimal locations for the EVCS. The second step aims to determine the optimal operating modes (expressed in \$ per kWh) of EVCS by modeling the variables of charging start time and charging time interval, which are uncertain in practice. In this case, boundary conditions were introduced to better describe the practical and technical state of the grid, such as the power flow: "A numerical analysis of the electric power flow in steady-state operation. Power flow study determines voltage angles and magnitudes at buses in power system for specified load demand, real power and voltage magnitude of generators." (IGI Global), voltage deviation: "A sum of voltage deviations at all buses in the power system from reference values. It is an important index in operating the electric power system." (IGI Global) and line capacity. The purpose of these restrictions is to select sites that would not put too much strain on the existing power grid. In practice, the power grid where EVCS are to be installed will have its own characteristics. In particular, it is likely to have minimum and maximum values for power flow, voltage deviation, and line capacity. For example, the voltage of the j^{th} bus must be between the following values: $V_j^{min} < V_j < V_j^{max}$.

When considering the CSO perspective, costs are usually part of the objective function because they matter in a real investment context. The emphasis on costs versus revenues is especially the case when the owners are public entities (e.g., a city or region) as their goal would be to provide the most cost-effective charging infrastructure possible for a given level of demand.

From the owner's point of view, a completely cost-independent objective function can also be considered, but this is less common. As far as we know, this specific approach has been used only once in the literature over time. It dates back to 2013, when Xi et al. tackled the problem of determining the ideal locations of electric vehicle charging stations in the Central Ohio region of the United States. They considered a linear programming optimization problem that aims to maximize the number of charging electric vehicles, which represents the success of a CS for owners. To obtain meaningful results, an important issue was modeling the electric vehicle fleet in the studied area, which was achieved by determining the probability of adoption of e-vehicles for potential users. For this purpose they used a linear model of the form $Y = X\beta + \epsilon$, where the probability of adoption (Y) was a function of demographic area as well as several other macroeconomic variables (represented in the model by the X). After estimating β, they obtained the adoption probability as a function of the demographic explanatory variables. They also introduced several restrictions in this paper that illustrate the market reality. In particular, one set of constraints was developed to account for peak demand in certain locations at a given time, and another aims to specify the budget within which service levels should be maximized. (A similar objective function was considered by Wang et al., 2018).

2.2 Distribution Network's Perspective

As mentioned above, this approach considers the perspective of the distribution networks, which would be responsible for meeting the charging demand of a certain area. Therefore, their main concern is the maintenance of the existing network and the costs of a new CS to the network when determining the optimal location for new EVCS (Ahmad et al., 2022).

This approach was studied very early when the problem of locating EVCS became important due to the emergence of EV. Rahman et al, 2013, were the first to address the problem. They used simulations to determine the EVCS locations that minimize the voltage sensitivity factor (VSF). This sensitivity is calculated as follows: VSF $= ||\frac{dV}{dP}||$, with P being the total input power and V the input voltage. This is achieved by studying individually the changes on the VSF that the addition of a loading station to a previously selected potential location causes. A large sensitivity would imply that for a small change in the input power, a large change in voltage magnitude could be observed, which represents a burden for the network.

But, quickly, other more detailed objective functions were developed to tackle the problem with a better precision. Also in 2013, Pashajavid and Golkar proposed to locate CS within a specific commercial area with the aim of increasing the use of photovoltaic panels and decreasing the effects of the use of thermal vehicles. They considered the search for locations that minimize energy losses: "The quantity of electric energy generated or purchased that is not available for sale to end users, for resale, or for use by the utility load-serving entity, attributable to transmission, conversion, distribution, and unaccounted for losses." (Law Insider). They also sought to minimize the voltage deviation. The constraints they considered are interval constraints for the energy losses and the voltage deviation. Because of its high speed of convergence, a Particle Swarm Optimization (PSO) algorithm was used. The same technique was later used by Reddy and Selvajyothi as well as Gupta and Narayanankutty, 2020, to minimize the power loss cost. Another technique that has rapidly emerged in the literature about optimal placement for EVCS is the use of Genetic Algorithms (GA). Su et al., 2013, were among the first to use this technique, they used it to minimize the distribution energy loss cost within an area.

In 2018, Aljanad et al. decided to pose this objective function in such a way as to use the vehicule-to-grid (V2G)[1] technology to minimize line loadings, which is depicted as follows: $F = w_1.L_{loading} + w_2.VD + w_3.CP_{loss}$ Where w_i are the weights granted to the different sub-objectives, $L_{loading}$ is is the thermal line loading effect: "Amount of heat (sensible and latent) energy to be removed from an inner environment by the refrigeration equipment to maintain that environment at

[1] Technology that aims to operate vehicles on charge either by feeding their residual electricity back into the grid or by limiting their charging rate.

the design temperature when worst case external temperature is being experienced." (IGI Global), VD is the voltage deviation and CP_{loss} is the total circuit loss (similar to energy losses). These three components of the multi-objective function are intended to model the load of adding a CS to the existing power system by studying the electrical deviation that it would generate. The optimization program was subject to interval constraints for the three elements of the multi-objective function, each of these cannot be above or below certain values, due to the network specificity.

From then on, within this approach, only few new elements were studied to be introduced in the objective function. The research addressed more new methods of resolution in order to improve the techniques that had already been used.

Recently, several researches aimed at improving the performance of the PSO algorithm, for instance, by using the the Improved New Binary Particle Swarm Optimization (INBPSO). It aims at providing a better computation time and more precise solutions. This is the case for the research of Sengupta and Datta, 2021, who sought to minimize power loss and voltage deviation using INBPSO. Another problem with the PSO is the lack of certainty that the final solution is optimal, because it commonly falls into a local optimum in the later stage. The introduction of the Improved Harmonic Particle Swarm Optimization (IHPSO), aims at improving this ability by introducing the harmony search (HS) principle, which expands the search range in later stage. This was achieved by Liu et al., 2021 by applying this new technique to their multi-objective function, which is based on comprehensive profit, voltage quality and the fluctuation in system load.

2.3 Electric Vehicule User's Perspective

This final approach focuses on the user's approach since the location of the CSs is directly influencing their loading behavior. In the literature, only very little research is devoted to this approach.

One of them was proposed by Yi et al. (2019), who decided to put the user at the center of their objective function and therefore consider three main components: the user's convenience in charging, the user's cost in charging, and the user's time in charging. User convenience is represented by introducing the notion of empty trip distance D_r, which refers to the distance traveled from the request point to the nearest station. It is calculated as follows: $D_r = D_1 - D_2$. Where D_1 is the distance traveled when there is a demand for charging, and D_2 is the distance traveled when there is no demand for charging. Then, the charging price P is used to represent the charging cost for EV users. The latter is determined by setting an interval $[P_{min}, P_{max}]$, where the lower bound represents the minimum price acceptable to the investor and the upper bound corresponds to the cost of refueling thermal vehicles (assuming that EV charging is cheaper). Finally, the dwell time indicator W_s is used to model the user's charging time. It is determined using a queuing theory model where the successive arrival intervals and service time follow a negative exponential distribution and the model contains c parallel service points (M/M/c model).

Othman et al. (2020) considered a similar objective function as they sought to minimise user travel costs. However, they used a different technique as they used an Enhanced Heuristic Descent Gradient Algorithm (EHDG). This technique is said to be a middle ground between a genetic algorithm and the Descent Gradient Technique (DG). The latter proposes a way to find a minima by changing the parameters in the opposite direction of the gradient of the objective function. In other words, on the plane generated by the objective function, one goes down the gradient to find a minimum. Thus, the EHDG algorithm uses the two techniques mentioned above. It typically starts with the use of a GA algorithm and ends with the application of DG, to improve performance.

2.4 Mixed Pespectives

We have seen that the literature on the optimal placement problem for electric car charging stations can be classified into three main approaches: CSO approach, DN approach, EV users approach. However, when studying this problem with real-world data, it is important not to focus on only one of these three approaches, otherwise it would be quite restrictive. Thus, a lot of research has explored including several of them in their objective function (Ahmad et al., 2022). The objective of this section is to review the relevant literature.

CSO and DN Mixed Perspectives

In this section, a focus is made on literature that combined both the DN approach and the CSO approach.

The first paper that combines these two approaches appeared in 2013 by Liu et al. The latter sought to minimize the total costs generated by a CS, formally:

$$minf = \sum_{t=1}^{T} \frac{1}{(1+\eta)^t} [\sum_{i=1}^{N_{EVCS}} (C^I_{EVCSi}(t) + C^O_{EVCSi}(t) + C^M_{EVCSi}(t) + C^L_{PS}(t)] \tag{2.1}$$

(with η being the parameter that specifies the discount rate to obtain the present value of future cost, T being the number of years included in the computation and N_{EVCS} being the number of charging stations in the distribution system). They not only included the costs related to investment $C^I_{EVCSi}(t)$, operations C^O_{EVCSi} or maintenance $C^M_{EVCSi}(t)$ (CSI approach) but also the network loss costs $C^L_{PS}(t)$ (DN approach). They were rapidly followed by some research considering similar objective functions. For instance, El-Zonkoly et al., 2015, sought to minimize the overall energy cost of the system. They considered the following objective function:

$$minf = \sum_{t=1}^{N} [C_{loss}Ploss(t) + C_{grid}P_{grid}(t) + C_{DG}P_{DG} + C_{gr}Pgr(t)]. \tag{2.2}$$

In this equation $C_{loss}Ploss(t)$ represents the total cost of power loss, $C_{grid}P_{grid}(t)$ the total cost of energy imported from the grid to the distribution network, $C_{DG}P_{DG}$ the total cost of energy obtained from DG units and $C_{gr}Pgr(t)$ the total cost of garages charge or discharge (which is the cost of energy being supplied by the parking lots during charge or discharge to support the network). This approach doesn't fundamentally differs from the aforementioned streams of literature, where these quantities were constrained to belong to given intervals..

This approach has gained importance over time in the literature. Awasthi et al., 2017, sought to complement the objective function by adding land cost, station equipment, power loss and voltage profile, solving the problem using a hybrid of GA and PSO (similar research has been conducted by Mozafar et al., 2017 by Mohsenzadeh et al.,2018 and by Faddel et al., 2018 in this mixed approach as well). At this point, some research included new elements in their objective function such as adding a penalty for possibly not covering a portion of the load demand (Zhang et al., 2016) or taking into account the revenue of a V2G (Moradijoz et al., 2018).

In 2019, two papers that used this approach developed new resolution techniques. The first, namely Deb et al. (2019), consisted of a hybrid method between chicken swarm optimization and TLBO (teaching-learning based optimization). The hybrid between the two aims to increase the convergence speed and usage rate. The second method is called Gray Wolf Optimization (GWO), Shukla et al. (2019), it was developed by Mirjalili et al. (2014). This hybrid tendency was also used by Deb et al. (2020), this time mixing the PSO and the TLBO algorithms.

Similarly, in 2021 Chen et al. and Pal et al., solved the optimal CS optimal location problem using the Balanced Mayfly Algorithm (BMA) and Harris Hawks Optimization (HHO) technique respectively.

To date, this remains the most studied mixed-approach in the literature.

CSO and EV users Mixed Perspectives

In this section a focus is made on articles that have combined both the CSO approach and the EV users approach.

The earliest studies on this mixed approach did not emerge until 2016. Indeed, the first were Zhu et al. They addressed the problem of minimizing construction costs and, at the same time, access costs (translating the convenience) for users by using a GA. Formally,

$$min \;\; \omega_1 . \sum_{j \in N} C_j . n_j + \omega_2 . \sum_{i \in N} \sum_{j \in N} K . d_{ij} . Y_{ij} . m_i \tag{2.3}$$

With $\omega_{1,2}$ being the weights granted to the different part of the objective function, C_j the unit cost of installing a charger at location j, n_j the number of chargers at location j, K the access cost per km, d_{ij} the distance from i to j, Y_{ij} a binary variable that is 1 if a region i traveler choose to charge in charging stations in region j, and 0 otherwise and m_i the number of EVs in region i. A constraint was introduced that required all vehicles to load in one region or another so that vehicles can only load in a region if there is a station at that location.

Another approach of this perspective was proposed by Zhu et al., (2018) in which they detail and further divide the objective function. Instead of only considering constructions costs, they include facility costs as well as management costs to their objective function (CSO approach), but regarding the EV Users perspective, they considered a very comparable expression. Similar objective functions were studied by Tian et al. (2018), Kong et al. (2019), Ren et al. (2019) and Luo and Qju (2020), also in that mixed approach.

CSO, DN and EV Users Mixed Perspectives

In this section a focus is made on literature that have combined the three approaches previously mentioned.

This combination of the three main approaches quickly appeared in the literature. For example, Moradijoz et al. (2013) and Sadeghi-Barzani et al. (2014) already included elements to represent power dissipation cost (DN), operating cost (CSO), and user convenience (EV users) in their objective function. Both solved the problem using a GA (a similar problem was also considered by Zhang et al., 2016 and Amini et al., 2017).

Luo et al. 2015 used a completely different technique than the one that has been used since the beginning of the researches about optimallocation of CS. They considered using a Bayesian Network to solve this placement problem. Strictly speaking, this is a machine learning method rather than an optimization technique. However, it ultimately provides an idea of the probability of selecting a potential site for the installation of a new charging station by considering criteria for the variables that influence the potential selection of a site. The greatest advantage of this technique is that it allows all types of variables to be considered when examining a particular site. For example, it is possible to consider ecological criteria that are directly related to a particular site (air quality at that site, the deviation of the drinking water network for construction at that site, and the analysis of waste generated by a potential construction are among the ecological variables that are often considered). This technique was also used by Hosseini and Sarder (2019). By using this technique, the researchers do not include real-world constraints in their model.

Battapothula et al., 2019 considered the application of NSGA-II (non-dominated sorting genetic algorithm) to solve the optimal placement problem in EVCS. The latter is a particularly popular algorithm for solving problems with a multi-objective function due to its high performance and ability to find an optimal solution.

2.5 The Literature in a Nutshell

In this chapter, much information, objective functions, and solution methods have been discussed. The purpose of this section is to summarize in a few words the most important information about the optimal placement of EVCS. In table 2.1, we give an overview of the different approaches, objective functions, boundary conditions, and related papers.

Currently, the vast majority of researches consider the CSO approach. For this reason, there is only one paper so far that describes the DN and the EV user perspective without considering the CSO perspective. Pazouki et al. (2013) are the only ones who have used this mixed approach. They consider an objective function that includes the cost of electricity loss (DN approach) incurred by a demand response (EV user approach). They solved the problem using a GA

To understand this classification, it is generally important to know that researches follow a certain perspective when it is considered in its objective function. In some of the papers we have discussed (notably Faridpak et al., 2019), one particular perspective is modeled while constraints are introduced for another. In these studies, we assume that only the modeled perspective is the one considered in the objective function.

Perspective	**Objective Function**	**References**
CSO	Construction costs, Installation costs, Investment costs, Operation costs, Number of EVs that load	Lam et al. 2014, Faridpak et al. 2019, Xi et al. 2013, Wang et al., 2018
DN	Voltage sensitivity (deviation), Energy losses, Power losses (costs), Thermal effect, Circuit losses	Rahman et al. 2013, Pashajavid and Golkar 2013, Reddy and Selvajyothi 2020, Gupta and Narayanankutty 2020, Su et al. 2013, Aljanad et al. 2018, Sengupta and Datta 2021, Liu et al. 2021
EV Users	Charging costs, Charging convenience, Charging time, Travelling costs	Yi et al. 2019, Othman et al. 2020
CSO and DN mixed	Operation costs and network loss costs, energy costs of the system	Liu et al. 2013, El-Zonkoly et al. 2015, Awasthi et al, Mozafar et al. 2017, Mohsenzadeh et al. 2018, Faddel et al. 2018, Zhang et al. 2016, Moradijoz et al. 2018, Deb et al. 2019, Shukla et al. 2019, Deb et al. 2020, Chen et al. 2021, Pal et al. 2021 .2017,
CSO and EV Users mixed	Construction (Facility, Management) costs and Access (Station access, Waiting) costs	Zhu et al. 2016, Zhu et al. 2018, Tian et al. 2018, Kong et al. 2019, Ren et al. 2019, Luo and Qju 2020
DN and EV Users mixed	Power loss cost generated by demand response	Pazouki et al. 2013
CSO, DN and EV Users	Power loss costs, convenience costs and operation costs	Moradijoz et al. 2013, Sadeghi-Barzani et al. 2014, Zhang et al. 2016, Luo et al. 2015, Hosseini and Sarder 2019, Battapothula et al. 2019,

Table 2.1: Summary of the literature

Chapter 3

Models

The objective of this section is to introduce the procedure and mathematical models that are used to address optimal placement of charging stations in the city of Brussels. The method used is based on the one proposed by Deb et al. (2019), i.e., a two-step process to find the best locations for CS within the city of Guwahati, India. The first step is detailed in Section 3.1, which consists of an evaluation of potential locations using a probabilistic approach. The second step aims to find the best locations from those previously evaluated. The details of the elements introduced in the objective function are the subject of the section 3.2. We describe and classify them according to the perspective they take in the optimization problem. Eventually, in Section 3.3 we introduce a heuristic procedure that can be used to approach the solution of the optimization problem describe in section 3.2.

3.1 Evaluation Of Candidate Locations

In the framework of this thesis, a probabilistic approach is used to evaluate a candidate site for the implementation of a charging station. A common practice in determining candidate sites for a CS is to analyze sites located at the intersection of the electricity distribution network and a node of the road network (Deb et al., 2017; Wang et al., 2013). However, in the context of the city of Brussels, this definition does not correspond to the reality of the network structure. Indeed, this definition would only be applicable to potential sites in the extra-urban environment and therefore not to sites within the city of Brussels. Using this definition to determine the sample of potential sites would lead us to consider too many possible load points, as the intersections between the roads and the distribution network in the city are numerous. Therefore, to better reflect the reality of the network, we define all parking lots in the Brussels-Capital Region as potential locations.

When considering the problem of optimal location of loading stations, a large number of variables (both qualitative and quantitative) can be taken into account. We decided to perform a preliminary evaluation of candidate locations in order to take into account some of these qualitative variables. The implementation of such an approach allows, therefore, to introduce new elements that were not part of the three main perspectives presented in the literature review.

We decided to introduce two qualitative criteria to assess the quality of a candidate location.

As Hosseini et al. (2019) note, and as we have seen in the literature review, none of the studies so far have considered the environmental criterion in the context of the problem of optimal location of charging stations for EV. In this paper, we decided to include this criterion in the decision-making process by introducing the air quality variable in the evaluation procedure. Thus, locations where the air quality is worse than other locations are preferred, assuming that this would encourage users to choose an electric vehicle or public authorities to prioritize these ares for development charging infrastructures. This change of vehicle by users would in turn lead to an improvement in air quality.

We also consider what we call a 'social' criterion. The first variable affecting this criterion is the population density. Here, preference is given to locations with high population density, since it is assumed that high population density also results in high demand for charging infrastructure. The second variable of the social criterion is the average per capita income. We know that EV are on average more expensive to purchase than conventional vehicles. This variable therefore allows us to favor the locations in Brussels where the purchasing power is comparatively higher, since we assume that more vehicles need to be charged in such locations. An overview of the probabilistic network is given in the figure (3.1).

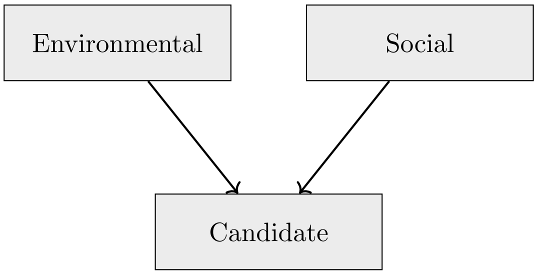

Figure 3.1: Network representation of the probabilistic evaluation for potential locations

We note that the node 'candidate' is the child node of the parent nodes 'environmental criterion' and 'social criterion'. All of these criteria are modelled as binary variables that measure a dichotomous response {'True', 'False'} depending on whether they meet the criteria we define in the next section. The candidate variable can also take the values True and False. Therefore, the probability that a given location takes the value 'True' (is evaluated as a good candidate) is given by Eq. (4.1).

$$\begin{aligned}\mathbb{P}(\text{Candidate} = \text{True}) = &\\ &\omega_1 \cdot \mathbb{P}(\text{Environmental criterion} = \text{True}) + \\ &\omega_2 \cdot \mathbb{P}(\text{Social criterion} = \text{True})\end{aligned} \tag{3.1}$$

With $w_1, w_2 \in [0, 1]$ and $w_1 + w_2 = 1$ being the weight assigned to the i^{th} screening criterion according to the importance we attach to it. We will determine these weights in the next chapter.

The air quality factor under the environmental criterion is based on two air quality variables: the PM10 index, which indicates the concentration (expressed in $\mu g/m^3$) of fine particles smaller than 10 micrometres, and the concentration (mg/m^3) of carbon monoxide (CO).

To determine the value of the social criterion as ‘True’, a probability-based approach is again used, since it depends on two different variables. An illustration of this network can be found in Fig. (3.2).

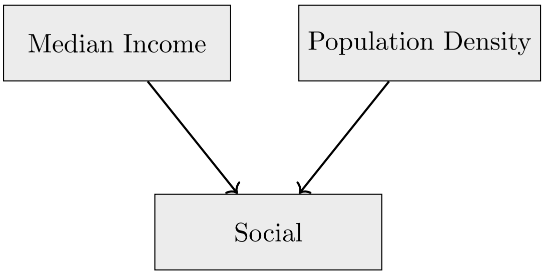

Figure 3.2: Network representation for the social criterion

For the social criterion to be set to ‘True’, the median income per capita must be above a fixed value and population density must already be above a certain threshold. These two values will be determined in the next chapter of this paper based on the characteristics of the city of Brussels.

3.2 Formalized Problem Statement

3.2.1 The Envisaged Perspectives

As outlined in Chapter 2, the problem of optimal positioning of charging stations can be considered mainly from three perspectives: from the perspective of CSO, from the perspective of DN, and from the perspective of EV users. However, considering only one of these perspectives may be too limiting. Therefore, we decided to consider two of these approaches, namely the CSO perspective and the EV user perspective (while the DN perspective is introduced in the constraints). The goal of this section is to describe individually the elements to be considered and how they enable a particular perspective to taken into account.

Charging Station Owner’s Perspective

The first perspective we consider is that of CSO. In this approach, it is the cost that makes up the objective function most of the time. It is therefore necessary to model the costs they face. Here, the costs faced by charging station owners are modelled as follows (based on the definition of Deb et al., 2019):

$$TI_i = IC_i + OC_i \tag{3.2}$$

Which can be further developed:

$$IC_i = f_i \cdot C_{fast} + s_i \cdot C_{slow} \tag{3.3}$$

And:

$$OC_i = \{f_i \cdot CP_{fast} + s_i \cdot CP_{slow}\} \cdot P_{elec} + RC_i \cdot \{f_i + s_i\} \tag{3.4}$$

With $i = 1, 2, ..., I \in \mathcal{I}$ the set of potential locations.

Variables	**Definition**
f_i	Number of fast charging points in station i
s_i	Number of slow charging points in station i
Parameters	**Definition**
TI_i	Total investment for installing a station at location i
IC_i	Installation cost of station i
OC_i	Operation cost of station i
RC_i	Monthly rental cost of a parking spot in station i
$CP_{fast,slow}$	Power consumption of fast or slow charging points
$C_{fast,slow}$	Unit cost of installing a fast or slow charging point
P_{elec}	Per unit cost of electricity

Table 3.1: Variables and parameters of the total investment expression

Eq. (3.3) shows that the cost of installing a charging station depends directly on the number of fast and slow charging points to be installed, as well as the average rental cost of a parking lot in the municipality where the new charging station are located. Eq. (3.4) shows that the operating costs also depend on the number of fast and slow charging points, their consumption, and the unit cost of electricity.

We have chosen this expression for modelling the perspective CSO because it provides a simple and intuitive yet realistic proposal for the different types of costs (investment and operating costs). Note that revenues are note taken into account for two main reasons: the literature rarely includes the revenues modeling and we could consider this approach as being the one of a public investor.

EV Users Perspective

As we have seen in the literature review section, few papers in the past have addressed the EV user perspective, either from a dedicated or mixed perspective. In this work, we have chosen to use a modeling approach similar to the one proposed by Zhu et al. (2016). In their paper, they propose to optimize charging station locations by considering both the perspective of CSI (by including construction costs in the objective function) and EV users. However, we only include the part related to EV users.

A common approach in considering this perspective is to minimize the sum of distances between any given location and the nearest charging station. However, in a real-world context, simply considering distance could lead to results that are not representative of the user experience. For example, a short distance in an urban environment may mean a long and costly trip for the user under certain congestion conditions. Therefore, they propose to consider not only the distance but the total cost of access (see Eq. (4.2) for the formal definition of access cost per kilometer). What we find in this equation is an aim to limit the access cost of the stations to be added. For each potential site i, we sum the distances separating it from the centers of all municipalities k. Thus, we expect the selected sites to be located near the geographic center of the search area and not on the outer edges of the municipalities.

$$\sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} AC \cdot d_{i,k} \cdot m_k \tag{3.5}$$

With $i = 1, 2, ..., I \in \mathcal{I}$ the set of potential locations and $k = 1, 2, ..., K \in \mathcal{K}$ the set of municipalities that constitute the research area of this thesis: Brussels.

Parameters	**Definition**
AC	Access cost per kilometer
$d_{i,k}$	Distance between the candidate i and the center of municipality k
m_k	Number of EV users in the municipality k

Table 3.2: Parameters of the total cost of access

Another important value to be determined is the value of AC, the access cost per kilometer. The latter is estimated by considering the cost of a multi-modal transport that is incurred through a trip between the charging station and the user's destination, assuming that the user charges his electric car, travels home by public transportation, and returns later to pick up the car. In general, a user can consider three modes of transportation in the city of Brussels: taxi, bus, and metro (which also counts for the tramway, both being very similar). The calculation of this value is intended to approximate the cost of a kilometer driven in Brussels (other than by car). Thus, the access cost can be determined by the following expression:

$$AC = \omega_1 \cdot C_{taxi} + \omega_2 \cdot C_{bus} + \omega_3 \cdot C_{metro} + C_p \tag{3.6}$$

With:

Parameters	**Definition**
C_{taxi}	Cost per kilometer of taking the taxi
C_{bus}	Cost per kilometer of taking a bus
C_{metro}	Cost per kilometer of taking a metro
C_p	Penalty cost
$\omega_{1,2,3} \in [0, 1]$	Proportion of individuals taking the taxi, the bus and the metro

Table 3.3: Parameters of the access cost computation

From this expression, the access cost per kilometer can be derived. This value is calculated in the following sections based on data specific to the city and EV users in Brussels.

3.2.2 Mathematical Formulation Of The Problem

In the previous subsection, we described individually all the elements of the perspectives that are included in the objective function. This subsection is therefore devoted to the formal construction of the model that is used in the rest of this paper.

The cost function to be minimized is, therefore, the following:

$$\omega_1 \sum_{i\in\mathcal{I}} f_i \cdot C_{fast} + s_i \cdot C_{slow} + \{f_i \cdot CP_{fast} + s_i \cdot CP_{slow}\} \cdot P_{elec} + RC_i \cdot \{f_i + s_i\} + \omega_2 \sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{I}} AC \cdot d_{i,k} \cdot m_k \cdot X_i \tag{3.7}$$

Or in its condensed form:

$$\begin{aligned}
\text{minimize} \quad & \omega_1 \sum_{i\in\mathcal{I}} TI_i + \omega_2 \sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{I}} AC \cdot d_{i,k} \cdot m_k \cdot X_i && && (3.8a)\\
\text{subject to} \quad & s_i \in \{0,1,2,3,4,5,6\} && \forall\, i \in \mathcal{I}, && (3.8b)\\
& f_i \in \{0,1,2,3\} && \forall\, i \in \mathcal{I}, && (3.8c)\\
& s_i + f_i \leq 6 \cdot X_i && \forall\, i \in \mathcal{I}, && (3.8d)\\
& s_i + f_i \geq X_i && \forall\, i \in \mathcal{I}, && (3.8e)\\
& \sum_{i\in\mathcal{I}} (1.5 f_i + s_i) \geq \frac{\text{M}}{640}, && && (3.8f)\\
& \sum_{i\in\mathcal{I}} X_i \geq 19, && && (3.8g)\\
& X_i \in \{0,1\} && \forall\, i \in \mathcal{I} && (3.8h)
\end{aligned}$$

Where M is the total number of EV users in the city of Brussels, we will determine its value in the next chapter, $i = 1, 2, ..., I \in \mathcal{I}$ the set of potential locations and $w_1, w_2 \in [0,1]$ and $w_1 + w_2 = 1$ being the weight assigned to each of the terms.

Thus, the objective function described in Eq. (3.8a) considers the following two terms:

1. Minimize the total installation and operation costs.
2. Minimize the total user access cost and thus maximize its convenience.

Under constraints explained in Table 3.4.

The way we model the second part of the objective function in this paper requires further explanation. Namely, it is clear that opening an additional location increases the total access cost. Therefore, opening a new location is not exclusively minimal. In practice however, the more stations that are activated, the less distance the user has to travel to reach the nearest station, resulting in lower (average) access costs for the user. It is important to be aware of this so that it does not cause a problem in the interpretation of the model. In our model, we first select a certain number of stations (at least 19, constraint 3.8g) and continue the selection until the demand is met (constraint 3.8f), and we add these stations in such a way that the total additional access cost of adding these stations is as small as possible compared to the cost that would have been incurred if other locations had been selected.

One of the constraints also deserves a more detailed explanation, namely Eq. (3.8d). A study of the Brussels case has shown that the electricity distribution network is robust enough to support the strategy of installing charging stations (Electrify.Brussels, 2022)[1]. This is true regardless of the location considered for the installation of a new station, even if it is geographically distant from the electricity grid. We therefore decided not to directly consider the DN perspective in the optimization program. The only constraint to be considered in the study of this perspective in the case of Brussels is that the number of charging stations cannot exceed a size of six chargers, with a maximum number of three fast chargers (constraint 3.8c). A station that removes these restrictions would require specialized and non-standard facilities to carry the load, and most importantly, it would require a large parking lot, which would put significant pressure on parking spaces for non-EV users, which is the main challenge of the Brussels charging station strategy.

It should also be noted that constraint 3.8g does not contain any requirements for area coverage within municipalities. In fact, there is nothing to prevent two stations from being very close to each other or even being in the same location. In our case, if two stations are the best alternative for low-cost access and are geographically close, we choose both. In practice, we could decide to cover the entire geographic area by mandating that at least one station be opened per municipality, or more precisely, by covering different areas (north and south) within a municipality (for example, by imposing a minimum distance between two selected stations).

[1] This information was confirmed following a call with Mr. Nicolas Spilleboudt, Manager Green Mobility at Sibelga, corporation responsible for the electricity distribution network for the city of Brussels.

Constraints	**Definition**
3.8b	The number of slow chargers installed at location i is in the range of 0 to 6
3.8c	The number of fast chargers installed at location i is in the range of 0 to 3
3.8d	Chargers can only be installed at activated locations and when the station i is activated, there cannot be more than six chargers installed
3.8e	When stations are activated, at least one charger is installed
3.8f	There is at least one charger for 640 users in the Brussels-Capital Region, a fast charger charging 1,5 times faster than a slow charger
3.8g	There are at least 19 stations installed. This represents an average of one station per municipality. However, there may be no stations activated in some municipalities. This restriction is not likely to be a hard constraint. However, it does highlight the arbitrary decision to install a certain number of stations in the search area.
3.8h	X_i is a binary variable which indicates whether a station is installed at the location i

Table 3.4: Explanation of the constraints of the optimisation problem

3.3 Heuristic Approach

We have just presented the model that will be optimized in the next chapters of this thesis. The goal of this section is to develop a heuristic approach that attempts to approach the solution through logical reasoning. In this section, we will describe the steps of this heuristic and the intuition behind its construction. Indeed, in a real implementation context with a large amount of data, obtaining a solution via an exact solution procedure (using a solver), can be computationally heavy. The objective of the introduction of this heuristic is to present a procedure that is much less computationally expensive and that, as we will see, allows to approach the exact solution.

When analyzing the final objective function, it is noticeable that there are two main elements that distinguish between two stations (i and j) when deciding whether to install a station: the cost of a monthly rent at these locations i and j (RC_i and RC_j) and the distances between stations i and j and the centers of the municipalities (d_{ik} and d_{jk}). The main part of the heuristic from now are based on these two elements.

The heuristic is divided into two main steps, a preprocessing and the heuristic itself. The first step is to create the features needed for the second step:

1. Preprocessing
   (a) Initialize the input: the set of the candidate locations
   (b) For each of these locations $i = 1, 2, 3, ..., I \in \mathcal{I}$, compute the average distance between the location and all the center of municipalities:
   $$\overline{d_i} = \frac{\sum_{i=1}^{I} d_{ik}}{K} \tag{3.9}$$
   (c) Compute the rescaled average distances (RAD) for each of the candidate locations so that the smallest average distance becomes 0,1 and the largest becomes 1:
   $$\mathrm{RAD}_i = (\frac{\overline{d_i} - \min(\overline{d}_{i=1,2,...,I})}{\max(\overline{d}_{i=1,2,...,I}) - \min(\overline{d}_{i=1,2,...,I})}) \cdot 0,9 + 0,1 \tag{3.10}$$
   (d) Rescale the rental costs (RRC) for each location so that the smallest gets 0,1 and the biggest gets 1:
   $$\mathrm{RRC}_i = (\frac{\mathrm{RC}_i - \min(\mathrm{RC}_{i=1,2,...,I})}{\max(\mathrm{RC}_{i=1,2,...,I}) - \min(\mathrm{RC}_{i=1,2,...,I})}) \cdot 0,9 + 0,1 \tag{3.11}$$
   (e) For each location, compute a score (Score_i):
   $$\mathrm{Score}_i = \mathrm{RAD}_i \cdot \mathrm{RRC}_i \tag{3.12}$$
2. Heuristic Approach
   (a) Order the set of location according to Score_i
   (b) Take the 19 locations with the lowest score in order to satisfy the constraint 3.8g
   (c) Install a fixed combination of chargers at those locations but with at most 6 chargers (constraint 3.8d)
   (d) Keep selecting stations (and installing the same fixed combination) among the remaining candidates until the demand coverage constraint is fulfilled (constraint 3.8f)
   (e) When constraint 3.8f is fulfilled: return the candidate solution

This heuristic is a greedy heuristic that essentially solves the optimization problem by finding a locally optimal solution. For more information on greedy heuristics, see Vasco et al. (2016).

The goal of this heuristic is to select locations where, on average, installing a charging station is relatively inexpensive and accessible to users. Although it provides an approximation of the solution in terms of location, it is important to note that it does not provide an idea of the composition of the stations to be selected. Rather, it is based on the idea of installing a fixed combination of charging stations at a given location (possible fixed combinations are discussed in more detail in the next chapter).

Chapter 4

Data

This section contains explanations about the data used to solve the optimization problem. This chapter starts with the description of the research area, then follows the modeling of the probabilistic evaluation, and finally it describes real data used for the optimization. It is extremely important to remember that the focus of this thesis is on designing the optimization process rather than drawing conclusions from the data described in this chapter.

4.1 Geographic Area of Interest

As mentioned above, the city of Brussels is being analyzed. It is divided into 19 municipalities with different areas and populations, ranging from 188,000 inhabitants in the municipality of Brussels-City to 22,000 inhabitants in the municipality of Koekelberg. Together, they form the Brussels-Capital Region with an area of 161 km^2 and a total population of 1.2 million inhabitants. In addition to its inhabitants, the Belgian capital hosts hundreds of thousands of workers in its offices every day (about 400,000). All these data come from the website environnement.brussels (Environnement.Brussels, 2022)

The city of Brussels is served by numerous roads and highways, making it accessible from all sides. Within the Brussels-Capital Region, the most important roads are the small ring road, which surrounds the city center, and the large ring road, which delimits this region. Within the city limits of Brussels, it is also possible to get around by public transportation, which is also very well developed and offers travelers many options. The Brussels Metro has four lines serving the city center and surrounding suburbs, and the tramway has 17 lines. The Brussels bus network is also very dense, with over 50 lines. Finally, the city of Brussels can count on several shared mobility services (such as Uber or Bolt). Nevertheless the car is still the most used mode of transport for inner-city trips (Figure 4.1).

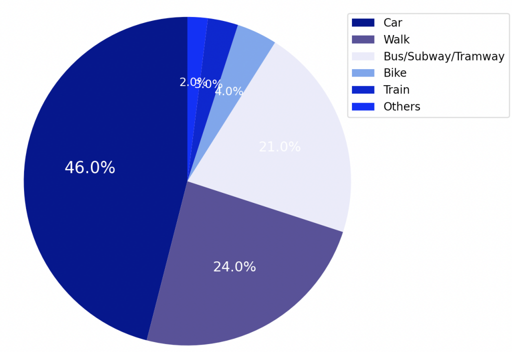

Figure 4.1: Intramural transportation in Brussels. Source: Environnement.Brussels

To sum up, Brussels is a city that welcomes a large number of workers every day, in addition to its inhabitants. There is no doubt that it needs a well-developed and efficient road and public transport network. The relatively small size of the city makes it easily accessible to workers and residents. Yet it is one of the most congested cities in Europe. This significant congestion on Brussels' road network leads to complications of various kinds. These include, of course, the increasing time it takes road users to go across Brussels, but also, as we know, the increase in fine particles concentrations in the air due to congestion. Finally, noise pollution caused by traffic jams is often cited as one of the main problems.

It is obvious that EV do not directly solve the problem of traffic congestion in the city of Brussels. However, they do solve some of the externalities caused by this congestion. Apart from the fact that they do not emit exhaust gases, the noise of an electric car is very low or even non-existent.

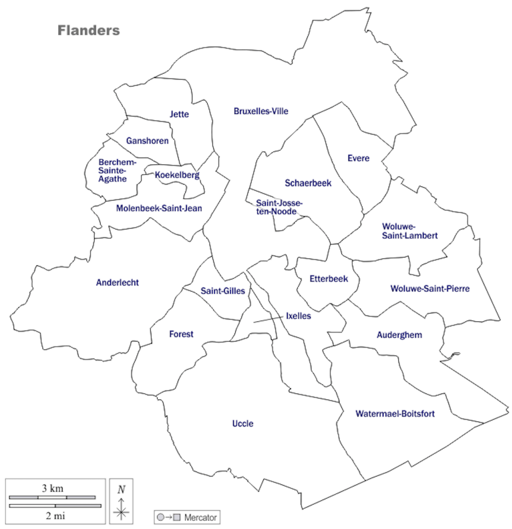

Figure 4.2: City of Brussels and delimitation of the 19 municipalities

4.2 Probabilistic Modeling

In this section, we explain the modeling procedure for the criteria introduced in the probabilistic evaluation. As a reminder, two criteria were considered in this modeling: the environmental and the social criteria. The objective of this approach is to evaluate the candidate sites based on these qualitative criteria, thus providing a first approach to determine the optimal sites. To model these, we examine three (random) variables (air quality for the environmental criterion, population density and median income for the social criterion). For each of these variables, we fit a statistical distribution that is assumed to represent them. These distributions are chosen based on common literature practices, their interpretability, or the simplicity of the calculations.

4.2.1 Environmental Criterion

For the modeling of this criterion, data from the website of 'environnement.Brussels' (FAQ — Air Quality, n.d) was used. The latter contains historical data of various air quality measurements at 14 measuring stations distributed in the Brussels area. The locations of theses stations have been chosen in order to represent the whole city of Brussels as well as all types of urban environments. It is finally thanks to pollumeters installed at these stations that data on air quality can be collected.

Variable Name	**Modeling Procedure**
PM10 level	TNORM ($\mu = 13,\ \sigma^2 = 2,\ LB = 4,\ UB = 26$)
CO level	TNORM ($\mu = 1,7,\ \sigma^2 = 1,07,\ LB = 0,1,\ UB = 7,7$)

Table 4.1: Modeling of the air quality variable

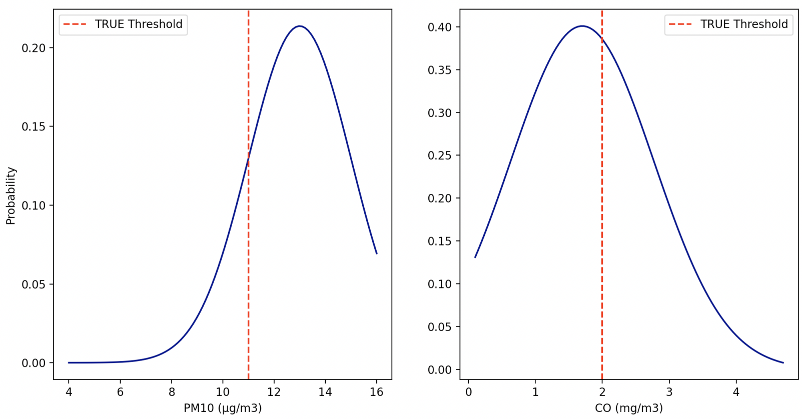

Figure 4.3: PM10 and CO distributions for the first candidate

For modeling air quality variables, common practice in the literature (Hosseini et al., 2019) suggest a truncated normal distribution. Table 4.1 illustrates the formal modeling procedure for the PM10 and CO variables for the first candidate[1]. It is then necessary to do the same for the other candidates by following the same logic. Similarly, Figure 4.3 illustrates these distributions graphically, showing the threshold above which each of the variables takes the value 'True'. Thus, when both variables take this value, it is the environmental criterion that takes the value 'True'. In this first candidate, it appears that the PM10 variable has a fairly high probability of taking the 'True' value. On the other hand, the CO variable certainly pull down the air quality factor, as we see in the figure. However, there is no certainty that this is also true for the other stations.

4.2.2 Social Criterion

As a reminder, we decided to use two variables to model the social criterion: population density and average per capita income. Clearly, the data for these two factors is difficult to obtain for each individual site. Therefore, we assume that the probabilities for accepting the value 'True' are the same for all candidate sites within the same municipality.

Data were collected through Brussels statistical website (Brussels Institute for Statistics and Analysis - IBSA, n.d.-b).

Population Density

In this paper, population density is modeled as a normal distribution for clarity and interpretability (Figure 4.2). Here, the value 'True' is given when the population density (per km^2) is above the average for the Brussels Region. An overview of the curve and the threshold is shown in Figure 4.4.

Variable Name	**Modeling Procedure**
Population Density	NORM ($\mu = 10234,\ \sigma^2 = 1459$)

Table 4.2: Modeling of the population density variable

Median Income

Finally, the modeling of the distribution of median annual income is shown in Figure 4.3. It is modeled as a truncated normal distribution. For computational reasons, the lower and upper limits of the distribution are the same for all sites. In reality, upper and lower limits can be determined for each individual municipality or, even better, for each locality (taking into account the median income in a narrow radius) The threshold at which the variable takes the value 'True' is equal to the median annual income in the entire Brussels region (Figure 4.5).

[1]In the table, μ represents the average, σ^2 the variance and LB, UB are respectively the lower and upper bounds of the truncated normal distribution.

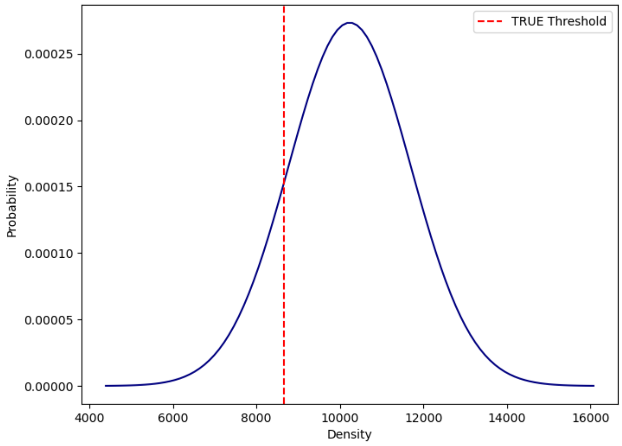

Figure 4.4: Population density distribution for the first candidate

Variable Name	**Modeling Procedure**
Median yearly income	TNORM ($\mu = 20160,\ \sigma^2 = 4200,\ LB = 10000,\ UB = 30000$)

Table 4.3: Modeling of the median yearly income variable

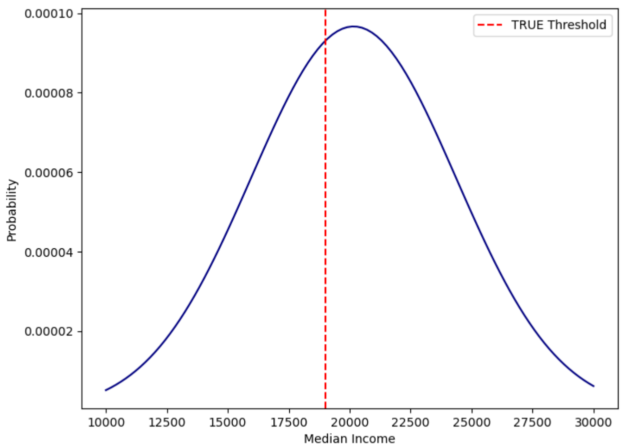

Figure 4.5: Median yearly income distribution for the first candidate

4.2.3 Probability Evaluation of the Candidate Location

The probability of a 'True' evaluation of a candidate site is the target node of the probabilistic network. This node is determined by the realization of the criteria that contribute to it: the environmental and the social criteria. As a reminder, the selection probability is calculated as the weighted sum of these contributing criteria (Eq. 4.1).

$$\begin{aligned}\mathbb{P}(\text{Candidate} = \text{True}) = \\ &\omega_1 \cdot \mathbb{P}(\text{Environmental criterion} = \text{True}) + \\ &\omega_2 \cdot \mathbb{P}(\text{Social criterion} = \text{True})\end{aligned} \tag{4.1}$$

With w_1 and $w_2 \in [0, 1]$.

In the following section we will analyze the changes in these weights and the impacts they may have on the evaluations of candidate locations.

4.3 Optimization Data

In this section we define and compute the values of all the constants we introduced in the model presented in the previous chapter. For clarity, they are treated in the same order as previously. In general, the constants are calculated to be as close as possible to the real conditions of electric vehicle charging. It is important to note that the accuracy of the calculations varies as the values of many of these constants depend on several (mostly macroeconomic) factors.

As mentioned earlier, the potential sites we consider in this paper are parking lots that are almost evenly distributed across the 19 Brussels municipalities. To date, there is no publicly available database listing the parking sites in the Brussels-Capital Region. It was therefore necessary to create a database with information about as many parking places in the study area as possible. For this reason, the database we created consists of a few observations (61). A larger database with more observations would have been desirable to improve the actual implementation of the approach. This small number of candidate sites implies that the maximum number of total EV users that our model can cover is equal to $\text{M} = 640 \cdot 6 \cdot 61 = 234\ 240$ users[2]. In order for the solution to distinguish the sites and truly find the best solutions among the candidate sites, we choose $\text{M} = 100\ 000$.

This dataset is not perfect, however it contains the necessary information to test a clear procedure and obtain results. The database contains general information about the parking lots: the name of the parking lot and the municipality where it is located, its geographical coordinates, its capacity, as well as the average cost of renting a parking space for a month.

Then it is necessary to define and calculate all the constants of the optimization problem.

Investment and operating costs

The first step is to analyze the constants of the total investment and operating cost function.

[2]Why 640? It takes an average of 45 minutes for an electric car to be charged, assuming that each user charge every other day and that only 10% of all charges are done on public charging infrastructures this gives: $\frac{24\text{hours}}{45\text{minutes}} \cdot 2 \cdot 10 = 640$

Parameters	**Value**
C_{slow}	1200€
C_{fast}	1500€
CP_{slow}	22kW
CP_{fast}	50kW
P_{elec}	0.26€/kWh

Table 4.4: Input parameters of the total cost expression

The values for power consumption correspond to the classic values found in the literature for differentiating between relatively slow and fast chargers.

It is important to note that costs can vary significantly depending on economic conditions (inflation, etc.) and also from one geographical area to another. Therefore, the costs we consider in determining the results may change, potentially affecting the optimal solution. Currently, the unit cost of equipment is determined by reviewing market bids for the installation of charging stations in 2023. The unit cost of electricity (in kWh) is an average of the tariffs offered by the major electricity suppliers in Belgium.

Access cost computation

Another constant to determine is the access cost per kilometer (AC).

Parameters	**Value**
C_{taxi}	2.6€
C_{bus}	1.5€
C_{metro}	1.3€

Table 4.5: Input parameters of the access cost expression

The equation is finally actually solved, with equal weighting of the three modes and a penalty of 0.5€:

$$AC = \frac{1}{3} \cdot 2.6€ + \frac{1}{3} \cdot 1.5€ + \frac{1}{3} \cdot 1.3€ + 0.5€ = 2.3€ \tag{4.2}$$

Again, it should be noted that while this value tends to reflect today's cost per kilometer, it can still change significantly. These values are based on widely available estimates of cost per kilometer for all three modes, but are subject to variation due to macroeconomic factors.

Distance Matrix

We now examine the construction of the distance matrix contained in the access cost expression. The latter has the following form:

$$\begin{pmatrix} \mathrm{d}_{1,1} & \mathrm{d}_{1,2} & \cdots & \mathrm{d}_{1,K} \\ \mathrm{d}_{2,1} & \mathrm{d}_{2,2} & \cdots & \mathrm{d}_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{d}_{I,1} & \mathrm{d}_{I,2} & \cdots & \mathrm{d}_{I,K} \end{pmatrix}$$

d_{ik} is assumed to be equal to 1 if station i is located in region k. The other distances are obtained by calculating the distance between the geographic coordinates of station i and the center of region k using the GeoPy library on Pyhton.

Users per municipality

Currently, there is no data on the exact number of electric vehicle users in each of the Brussels municipalities. Therefore we decided to approximate it as a function of two values: the number of inhabitants and the annual median income of the municipality. The number of users in a municipality can thus be approximately calculated as follows:

The first step is to rescale the data for the number of inhabitants and the median income so that they are between 0.1 and 1 (example for the population data):

$$\text{Scaled Population}_k = \frac{(0.9) \cdot \frac{\text{Population}_k}{\sum_{k=1}^{K} \text{Population}_k} + 0.1}{61} \tag{4.3}$$

It is then a matter of updating this value so that the sum of all these scaled populations on $\mathcal{K}$ equals 10,000:

$$\text{Scaled Population}_k = \left(\frac{\text{Population}_k}{\sum_{k=1}^{K} \text{Scaled Population}_k}\right) \cdot 100\ 000 \tag{4.4}$$

By performing a similar calculation for the annual median income data and with the following equation:

$$m_k = 0.25 \cdot \text{Scaled Population}_k + 0.75 \cdot \text{Scaled Income}_k \tag{4.5}$$

We have chosen to give more weight to scaled income. Indeed, purchasing power data seem to be important in the literature to determine the demand for charging (as in the work of Frade et al., 2011), while a large population density less directly imply a large demand.

It should be noted, however, that this approximation can by no means be considered perfect. Important assumptions are made in the calculation: the fact that the number of users depends only on the number of inhabitants and the median income, and the weighting of the income part against the population part. In practice, other elements can be taken into account for a more accurate approximation: the policies regarding electric transport in the municipalities, the presence of certain facilities that encourage the use of EVs, etc.

After the calculation, we obtain the number of users per municipality, which is shown in Table 4.6.

Municipality (k)	**Number of users** (m_k)	**Municipality (k)**	**Number of users** (m_k)
Anderlecht	4 670	Koekelberg	4 777
Auderghem	6 440	Molenbeek-Saint-Jean	4 815
Berchem-Sainte-Agathe	4 700	Saint-Gilles	4 793
Bruxelles-Ville	5 635	Saint-Josse-ten-Noode	4 210
Etterbeek	5 620	Schaerbeek	5 402
Evere	4 820	Uccle	6 358
Forest	4 880	Watermael-Boitsfort	5 715
Ganshoren	4 685	Woluwe-Saint-Lambert	5 873
Ixelles	6 265	Woluwe-Saint-Pierre	5 657
Jette	4 893		

Table 4.6: Approximation of users per municipality

Chapter 5

Results

This chapter describes the results obtained through the various methods previously introduced and enables to verify how the various steps of the optimization work in practice. First, in Section 5.1, the results of the preliminary evaluation of the candidate sites using a probabilistic approach are explained. We analyze the impact of the weighting of environmental and social criteria and then propose ways to find a solution based solely on this probabilistic assessment. Then, in Section 5.2, the performance of the previously described heuristic approach is discussed. Eventually, in Section 5.3, the results of the optimal solution approach and the differences with the heuristic solution are evaluated.

5.1 Probabilistic Evaluation Results

This section is devoted to the results obtained through the probabilistic approach developed in Chapter 3. First, the scores obtained when the weights for the social and environmental criteria are equal are examined. Then, the sensitivity to the changing weights of this probabilistic evaluation is analyzed.

5.1.1 Equal Weights

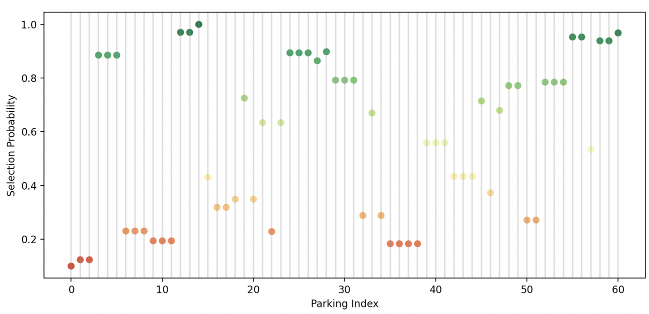

Figure 5.1: Evaluation probability for $w_{1,2} = 0.5$ (Equal weights for the social and environmental criteria)

First, we have the results of probabilistic evaluation of candidate with equal weighting of social and environmental criteria. It is noticeable that the evaluation seems rather well distributed but with still a little bit more locations with a probability close to the borders (0 and 1) than with an intermediate probability (0.5). This indicates that the variables introduced the evaluation process seem to take on relatively extreme values. For example, it is sufficient for the data for a particular location to take on one of the worst values in the sample for air quality, population density, or median income to pull the final probability down in the tail of the distribution, despite possible good probabilities for the other variables. It is also noticeable that at certain points in the graph, several locations receive the same final probability.

In this case, the locations that get a relatively good selection probability are located, on average, in a highly urbanized or industrial environment and with some intensity of road traffic (poor air quality), where the population density is high, and where the purchasing power (income) is higher than elsewhere, as can be seen in the Figure 5.1. The indices for the municipalities of Auderghem (4 to 6), Etterbeek (14 to 16), Ixelles (26 to 30) or Woluwe-Saint-Pierre (57 to 60) belong to the municipalities with the highest selection probability and meet the above criteria.

5.1.2 Changing Weights

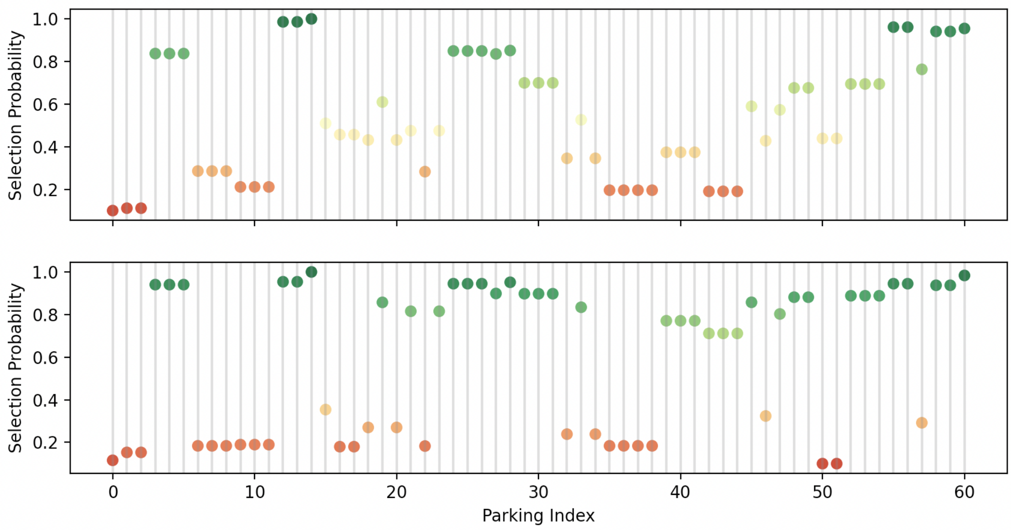

Figure 5.2: Evaluation probability for $w_1 = 0.25$, $w_2 = 0.75$ (top chart, greater importance of social criteria) and $w_1 = 0.75$, $w_2 = 0.25$ (bottom chart, greater importance of environmental criteria)

When analyzing the results after weighting changes suggested in Figure 5.2, it is noticeable that locations that already had a good score with the same weighting continue to have a high probability of selection (Audergem, Etterbeek, Ixelles and Woluwe-Saint-Pierre). However, the results of the evaluation are taking more values closer to 0 and 1 when the environmental criterion becomes more important. It seems that the concerns about the extreme values that one of the variables can take are confirmed. It seems that rather the environmental criterion pulls the ratings towards the edges

(0 and 1) than the social criterion.

In summary, real-world evaluations can be performed based on the variables introduced and modeled in this probabilistic approach. In some case studies, this can even be useful to screen potential locations and thus exclude some candidates from the optimization process. Here, we consider all candidates. This evaluation still helps us understand the environmental and social suitability of the optimal solution. Special attention must be paid to the values that the variables introduced into the network are likely to take, as these may artificially pull the final probabilities up or down.

5.1.3 Suggested Solution by the Probabilistic Evaluation

As we have just seen, we do not screen candidates based on the final probabilities obtained thanks to the probabilistic approach. However, in other implementation contexts with larger data sets, such an evaluation can be performed.

A first trivial approach is to arbitrarily set a probability threshold below which candidate sites are simply dropped from the database that is then used to run the optimization program. This approach is used by Deb et al. (2019) and is similar to that used by Hosseini et al. (2019)[1]. A second approach we might consider is to weight the score computed by each site under the heuristic approach (detailed in Section 3.3) by the selection probability. The score of each site would then be as follows:

$$\text{Score}_i = \text{RAD}_i \cdot \text{RRC}_i \cdot (1 - \mathbb{P}(\text{Selection}_i)) \tag{5.1}$$

This would possibly move the total cost of the heuristic solution away from that of the so-called optimal solution (since the solutions selected by the heuristic would no longer depend only on the parameters directly related to the objective function), but it would be possible to incorporate the probabilistic evaluation directly into the decision process of optimally locating CS.

Eventually, in this paper we propose a solution which is only based on the probabilistic evaluation. The procedure to obtain such a solution is very similar to the heuristic approach. Namely, we select the sites with the best results until we reach a coverage of the demand. However, to simplify the calculations, we only consider the fixed composition of six slow chargers per station. The key metrics of this solution are shown in the Table 5.1.

Note that the results are based on the probabilistic evaluation with a greater weighting of the social criterion, as this seemed to be the most balanced of the three alternatives discussed in the previous section.

[1] They decided to base their study solely on a BN and consider as optimal those sites whose probability is above a certain threshold

Metric	Value
Number of selected stations	27
Number of slow chargers installed	$27 \cdot 6 = 162$
Number of fast chargers installed	0
Total Cost	34 509 666€

Table 5.1: Key metrics of the solution suggested by the probabilistic evaluation

With the following evaluation:

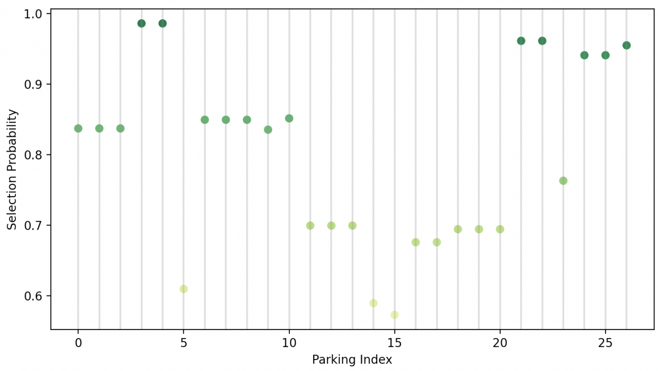

Figure 5.3: Selection probability of the solution suggested by the probabilistic evaluation

Of course, analysing this solution, we notice that all selection probabilities are relatively good (above 0.5). This proposal is a very acceptable solution. It is the one that receives the best score. In an implementation context where only qualitative criteria are considered, this procedure can be used to find the locations for the CS.

5.2 Heuristic Solution

The goal of this section is to describe the approximation to the optimal solution obtained by implementing the heuristic described in Section 3.3. The heuristic relies on an important assumption: the fixed composition of the selected charging stations. It assumes three fixed compositions. The first considers only slow chargers, the second only fast chargers, and the third a hybrid composition with 3 slow chargers and 3 fast chargers per selected site. Here, we analyze the results obtained by running the heuristic with these three fixed compositions.

5.2.1 Slow Chargers Only

The first fixed composition we consider is the one that prescribes to install 6 slow chargers at each site we choose until the demand is met. If we follow the steps of the heuristic and impose this composition constraint, we get the following results:

Metric	Value
Number of selected stations	26
Number of slow chargers installed	$26 \cdot 6 = 156$
Number of fast chargers installed	0
Total Cost	32 815 855€

Table 5.2: Key metrics of the slow chargers composition

This alternative offers a very reasonable and practical solution. In practice, we can imagine stations that have this fixed composition with only slow chargers. However, it should be noted that this proposal does not include a fast charging option throughout the search area. This could be problematic for some users. In addition, offering only slow-charging infrastructure increases pressure on parking lots due to low fluctuation in parking lot occupancy. As we saw in the chapter devoted to models, one of the biggest challenges in the deployment of CS in Brussels is the speed of deployment. Too rapid a roll-out would put too much pressure on thermal vehicles parking (monopolising too many parking spaces for charging). Therefore, it is important to design stations to allow for a good turnover of occupied parking spaces.

We decided not to show the probabilistic evaluation of this solution since it is not the best alternative solution proposed by the heuristic.

5.2.2 Fast Chargers Only

The second fixed composition we study is the one that requires only the installation of fast chargers (3 per site). It leads to the following results:

Metric	Value
Number of selected stations	52
Number of slow chargers installed	0
Number of fast chargers installed	$52 \cdot 3 = 156$
Total Cost	64 720 644€

Table 5.3: Key metrics of the fast chargers composition

It is noteworthy that the total cost of this solution is 35.09% higher than that of the solution with the slow charger. Moreover, this solution is not really feasible in practice. Indeed, stations consisting only of fast chargers would not allow to satisfy the basic needs of residents (e.g., neighborhood residents) and would force too much parking rotation, unlike stations consisting only of slow chargers.

Once again, we decided not to show the probabilistic evaluation of this solution since it is not the best alternative solution proposed by the heuristic.

5.2.3 Hybrid Composition

Finally, we consider a hybrid fixed composition between fast and slow chargers (3 each). This hybrid composition is more representative of existing stations in a real CS deployment context. It leads to the following results:

Metric	**Value**
Number of selected stations	20
Number of slow chargers installed	$21 \cdot 3 = 63$
Number of fast chargers installed	$21 \cdot 3 = 63$
Total Cost	26 404 240€

Table 5.4: Key metrics of the hybrid composition

This solution not only provides a practical solution, but is also the best compared to other heuristic solutions. It reduces the total cost by 59,2% compared to the solution with fast chargers and by 24,28% compared to the solution with slow chargers. This solution satisfies the basic demand of the users, called 'residents', thanks to the slow chargers and still allows a rotation of the parking lot thanks to the installation of fast chargers.

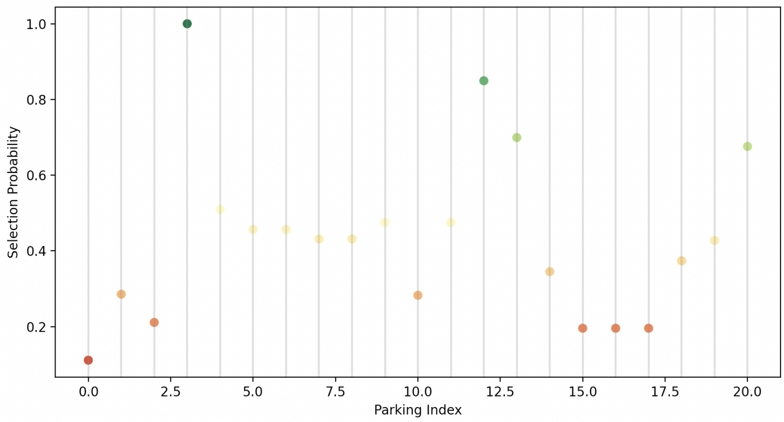

Figure 5.4: Selection probability of the heuristic solution with the fixed composition of 3 slow chargers and 3 fast chargers

We note that the sites selected by the heuristic perform poorly on average in the probabilistic view. In fact, only 8 of the 24 selected sites receive a selection probability above 0.5, so this information can be taken into account when other than economic concerns are considered (e.g., environmental criteria). A possible explanation lies in the fact that the sites selected by the heuristic have, among other things, relatively low monthly rental costs (RC). And most often, these relatively low-cost parking sites are located in communities where purchasing power (median annual income) is lower than elsewhere.

In the next section we will compare the results we obtained by running this heuristic to more optimal solutions to determine their quality. Moreover, there are real differences between the solutions for different fixed compositions. The mixed composition offers the lowest total cost, which confirms the interest in this solution that would provide charging infrastructure for all types of users. However, it should be noted that the probabilistic evaluation of this solution is not as good as the quantitative results.

Alternative Score Based on the Probabilistic Evaluation

As suggested in Subsection 5.1.3. A new version of the score (Eq. 5.2) can be computed based on the results of the probabilistic evaluation. By computing the score based on this new formulation.

$$\text{Score}_i = \text{RAD}_i \cdot \text{RRC}_i \cdot (1 - \mathbb{P}(\text{Selection}_i)) \tag{5.2}$$

We obtain the following results:

Metric	**Value**
Number of selected stations	24
Number of slow chargers installed	$21 \cdot 3 = 63$
Number of fast chargers installed	$21 \cdot 3 = 63$
Total Cost	24 152 668€

Table 5.5: Key metrics of the heuristic solution balanced with the probabilistic evaluation score

With the following evaluation:

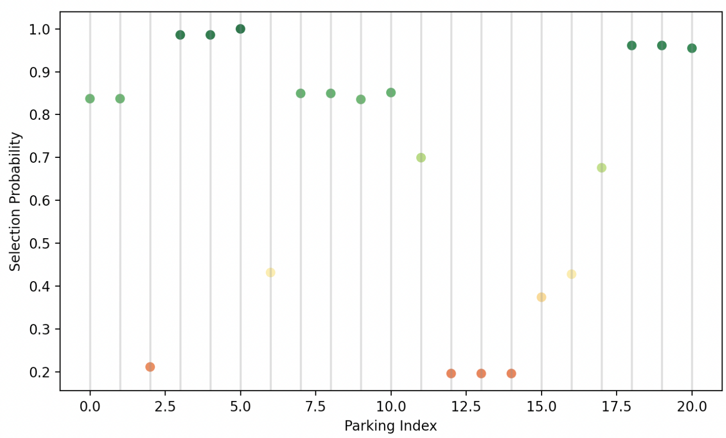

Figure 5.5: Alternative selection probability of the heuristic solution with the fixed composition of 3 slow chargers and 3 fast chargers

From the analysis of the metrics in Table 5.5 and the corresponding probabilistic assessment (Figure 5.5), it can be seen that the assessment of the selected sites can be significantly improved, while the cost function does not deteriorate significantly. Indeed, we note that 14 out of 21 scores are now above 0.5 (compared to 7 out of 21 in Figure 5.4) and even that total costs have decreased by 8.52%. This can be explained by the fact that the probabilistic evaluation captures part of the effects of parameters that are not initially introduced in the heuristic (such as the number of users taking into account the population density). This confirms the relevance of the approach, which consists in weighting the score of the heuristic based on the results of the probabilistic evaluation.

5.3 Optimal Solution

This section is devoted to the analysis and discussion of the solution obtained with a solver. In our case, the solver is the optimizer Gurobi, which we used through the Pyhton interface (in the rest of this paper, we call 'optimal solution' the one proposed by this solver). In a first step, we analyze the optimal results that can be obtained with it and compare these with the results obtained with the heuristic presented in section 5.2. Then we analyze and interpret the effects of varying some parameters on the optimal solution.

5.3.1 Optimal Solution

After setting up the necessary instructions to get a solution via the optimizer, we obtain the following results (Note that the program takes 120s to run):

Metric	**Value**
Number of selected stations	21
Number of slow chargers installed	62
Number of fast chargers installed	63
Total Cost	20 252 733€

Table 5.6: Key metrics of the optimal solution

The remarkable thing about this solution is that the total number of slow chargers installed is not the same as the number of fast chargers, resulting in a non-fixed composition between stations installed at optimal locations. Moreover, the probabilistic evaluation of the optimal locations is that shown in Figure 5.6. This result shows that the selected sites seem to have a good selection probability according to the qualitative criteria of the probabilistic evaluation. In fact, of the 21 sites selected, 12 have a selection probability greater than 0.5, indicating that the optimal solution also appears to be an environmentally and socially sound solution.

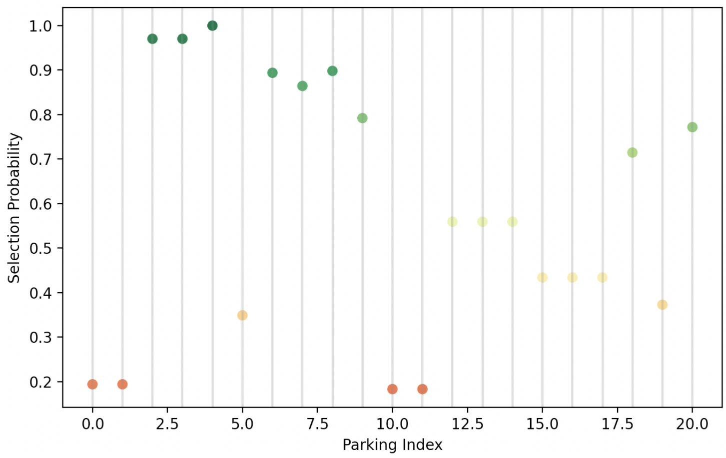

Figure 5.6: Selection probability of the optimal solution

5.3.2 Comparison Between the Optimal Solution and the Heuristic Solution

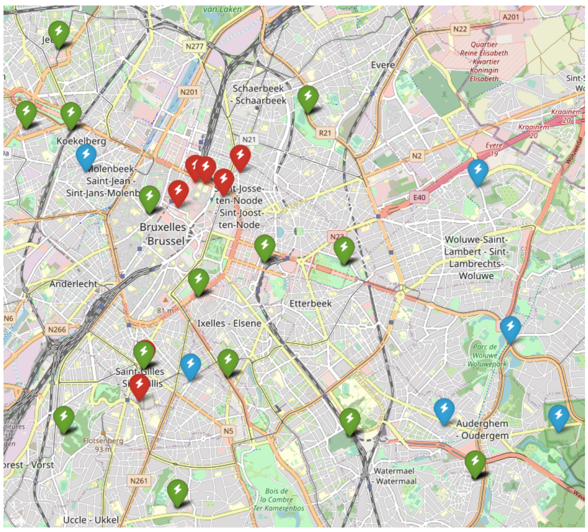

Figure 5.7: Comparison of the optimal and selected locations by the heuristic. Map built using the Folium library in Python.

The first points of comparison between the two solutions are, of course, the metrics (Table 5.5 and 5.6). The solution found with the solver has a lower total cost than the one obtained through the heuristic. This was to be expected, since the heuristic outputs a feasible solution that does not really guarantee good quality compared to the optical solutions. More specifically, despite the fact that it selects the same number of sites for the installation of stations, the optimal solution proposed by the solver allows a reduction of 16.14% in the total cost. This can be partly explained by the fact that this solution allows a non-fixed composition of slow and fast chargers, and therefore a total of 5 slow chargers less are installed than in the heuristic solution. In addition to this difference, the choice of locations is not the same. An overview of this difference is shown in Figure 5.8. On the map, the blue locations are those selected only by the heuristic, the red ones are those selected by the solver, and the green ones are those selected by both the heuristic and the solver. It is noticeable that even when the heuristic takes distance into account, the optimal solution favors the locations that are closer to the center (which by definition are accessible to all).

A final important element to consider when analysing the map is the presence of stations that are geographically close to each other. In a real implementation context, such a feature of the optimal solution should be considered. Indeed, we can imagine that adding a station next to an existing station has less impact on convenience than a station built in a location where the nearest existing stations are relatively inaccessible.

5.4 Sensitivity Analysis

The goal of this section is to study the effects of changes in certain parameters on the optimal solution. First, we examine how the distribution of slow and fast chargers changes when the unit cost of a slow charger varies. Then, we investigate the impact of varying the access cost on the selection of optimal locations. Finally, we examine the importance of the two perspectives of our optimal solution (that of the owners and that of the EV users) and the impact of weight changes in the objective function ($\omega_{1,2}$) on the optimal solution.

5.4.1 Unit Cost Variation

A characteristic feature of the optimal solution is that the stations do not have a fixed distribution between slow and fast chargers. Indeed, it can be observed that the total number of fast charging stations is greater than the number of slow charging stations. It therefore seems reasonable to analyse the reasons for this asymmetric composition. Intuitively, it can be assumed that this is due to the fact that the fast charger appears relatively cheaper in relation to its additional power (kW) compared to a slow charger. Indeed, if we compute, for example, the ratio between the unit cost of a charger and its power we obtain: $\frac{1500€}{50\text{kW}} = 30€/\text{kW}$ for fast chargers and $\frac{1200€}{22\text{kW}} = 54,5€/\text{kW}$ for slow chargers.

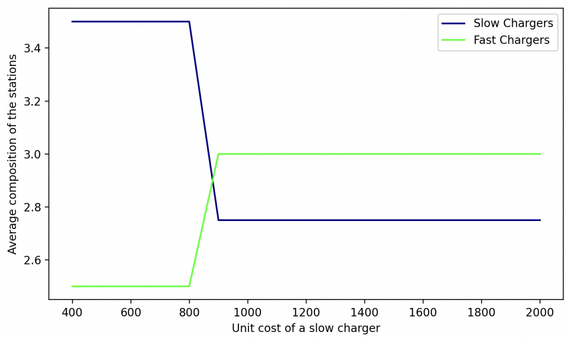

Figure 5.8: Average composition of stations with varying slow charger costs

The intuition is confirmed by the analysis of this diagram. In fact, it shows that the selected stations from a unit price of 900€ always have the maximum number of fast chargers allowed, i.e. 3. On the contrary, even if the unit cost of a slow charger is very low, no station consist only in slow chargers.

5.4.2 Access Cost Variation

Here we alter a parameter of the second part of the objective function and analyze the effects of its variation. Thus, we study the effects of varying the access cost per kilometer (AC) on the selection of the optimal site among candidates. Intuitively, one would assume that as the access cost per kilometer increases, the optimal sites are more likely to be found in the middle of the map (since they are more accessible on average).

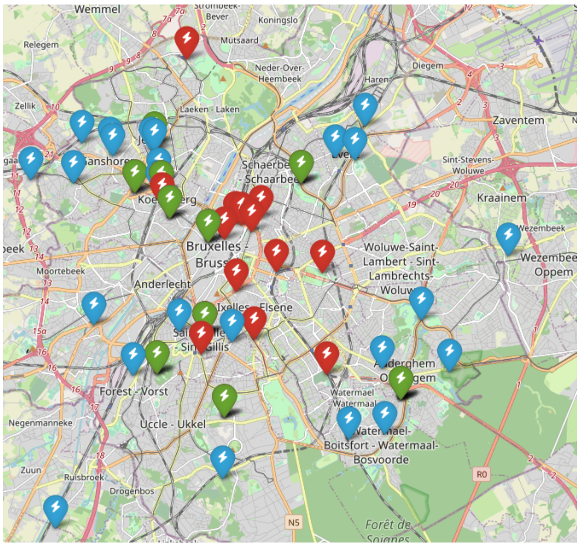

Figure 5.9: Optimal location with varying access cost. Map built using the Folium library in Python.

On the map, the places marked in blue are selected with AC $= 0$, the places marked in red are selected with AC $\neq 0$ (range of tested values between 0.5 and 5), and the places marked in green are selected in both cases

We notice immediately is that the optimal locations do not change as long as AC is different from 0, no matter how high its value. This perhaps indicates that the cost component is too important for the users of the objective function in the decision process for the optimal locations (further study of the impact of the access cost part of the total objective function is provided in the next subsection). When AC is set to 0, the differences appear because the optimization is done only from the perspective of the station owners. This leads to the selection of locations with the lowest monthly rental costs, which are usually further away from the center of the region.

5.4.3 Variation of the Objective Function's Weights

Our earlier analysis suggested that the share of user costs in total costs may be too high. In fact, variations in access cost per kilometer did not affect the selection of optimal sites. This subsection therefore examines the changes that can be observed when rebalancing the weights of the two perspectives in the calculation of total costs.

First, it is important to determine the extent of the imbalance:

$$\text{User's Perspective Proportion} = \frac{\text{User's perspective Cost}}{\text{Total Cost}} \tag{5.3}$$

Indeed, it has been found that the proportion of the user perspective is too large. In fact, 90% of the total cost of the measure is accounted for by this perspective. It is therefore necessary to rebalance the objective function so that it takes more account of the total investment.

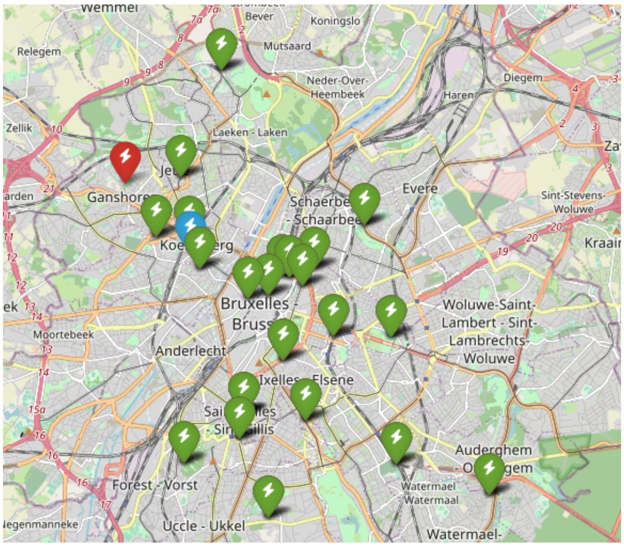

Figure 5.10: Optimal location with varying weights. Map built using the Folium library in Python.

The sites in blue are those that result when the weight of the owner perspective (ω_1) is 0.95 (in this case, the share of the owner perspective in the total cost is 0.67), in red are the initial optimal sites, and green are the sites selected in both cases. It is worth noting that regardless of the assigned weights, the optimal locations remain the same for the extreme majority, confirming the conclusions drawn earlier about the best locations.

Chapter 6

Conclusion

6.1 Summary and Main Contributions

Problem Summary

Recently, the problem of optimally locating and sizing charging stations has become more prominent with the increasing importance of more responsible modes of transportation. However, it is still a new topic, as the first study dates back only to 2011.

In this paper, this problem has been studied with the focus on designing a procedure to be followed combining qualitative and quantitative criteria. Our objective is to locate and size the charging stations to minimize costs while ensuring that the needs in the charging area are met. To define what is meant by an 'optimal location', several perspectives can be considered. The first is that of the owners of the charging stations. They will mainly look for locations that minimize investment costs. The second is that of the users. They will prefer locations that minimize access costs, i.e., the most accessible locations. Finally, there is the perspective of the electric distribution grid, which will select sites that minimize the impact on the electric grid.

Main Contributions

This thesis provides a multilevel procedure to approach the solution, which is close to the reality of the facts observed in the study area: the Brussels-Capital Region.

The first step of the process was performed through a probabilistic evaluation, aiming to get a first idea of the evaluation of the candidate locations, but based on qualitative criteria. In particular, an environmental criterion (modelled by air quality) and a social criterion (modelled by population density and median income per capita) were considered, resulting in an evaluation probability for each site. This probability can be taken into account in the optimization process by filtering out sites that do not reach a certain selection probability, or in deciding whether or not to implement certain stations at sites that receive a poor rating.

We then modeled the perspective of the owners and users in the main objective function developed in this thesis. We included the perspective of the distribution network in the constraints of the model but not in the function to be optimized. Indeed, a case study of the city of Brussels has shown that the network is robust enough to support the deployment of charging stations for years, as long as the stations do not exceed a size of six chargers to limit the strain not only on the network but also on the parking spaces for non-EV vehicles.

The exact solution for this objective function was then approached in two ways:

We first developed a heuristic. The steps of this heuristic are based on the parameters of the objective function that allow to distinguish one station from another. The problem of sizing the selected sites is more difficult to solve with heuristics. Therefore, we decided to run the heuristic with three fixed compositions of the selected stations and choose the most realistic one (with which the best results are obtained and the closer to what can be observable in reality).

Finally, an exact solution was obtained using a solver. This solution has been evaluated using the probabilistic approach. It turns out that, in general, is allows us to improve on the heuristic solution, but that the latter is a less time-consuming and computationally expensive alternative, while still providing an interesting approximation to the optimal solution.

Table 6.1 provides an overview about the total costs and the probabilistic evaluations of the proposed solutions.

Approach	**Total Cost**	**Average probabilistic Evaluation**
Probability evaluation based solution	34 509 666€	0.78
Heuristic solution	26 404 240€	0.43
Alternative heuristic solution (Probability based)	24 152 668€	0.67
Exact solution	20 252 733€	0.49

Table 6.1: Comparison of the main results

6.2 Limitations and Future Research Directions

We have developed several approaches to answer to the problem of optimal placement of charging stations in the Brussels-Capital Region. The different steps of this process were not spared from assumptions or constraints that represent limitations. Hence, this thesis should be viewed as a potential guide to charging station location. In this section, these constraints and limitations are explained in more detail.

Data Related Issues

In general, the main limitation of the whole process is the access to data and its accuracy. As mentioned before, there is no complete, accurate and accessible database of parking spaces or similar in the Brussels-Capital Region. Therefore, the database had to be built and the data was collected or created manually. Therefore, it cannot be guaranteed that the data is up-to-date and accurate.

As part of future research, first and foremost, one should make sure that reliable data is available. The point is to increase the time needed for data collection. Another approach to solving the problem of missing data may be data generation. An idea would be to generate a new candidate location a place in the middle of a line connecting two existing candidates and obtaining data on rental costs, air quality, median income, and population density by averaging data from these two existing candidates.

Probabilistic Evaluation

As for the probabilistic evaluation of the solutions, several elements can be considered as constraints. First of all, it is possible to improve the modeling of the social and environmental aspects by considering other variables to ensure a better modeling of these criteria. In our case, we considered the variables for which a relatively large amount of data was available. Other variables or criteria can also be considered for a more advanced probabilistic analysis. In addition, the overall modeling data for many candidate sites depended on the community in which they were located, so values for two sites in the same community were often very close (lack of granularity).

Heuristic Approach

As far as heuristics are concerned, the main limitations lie in the assumptions made. We have already discussed the fact that it is based on the assumption of a fixed composition, namely, 6 slow chargers, 6 fast chargers, or 3 chargers of each type.

Distribution Network Perspective

Although the case of the Brussels-Capital Region showed that this perspective is not mandatory, it could be interesting to add the DN perspective to the optimization process. Especially if it is no longer robust enough to support the strategy of introducing electric charging stations in Brussels. One approach in the literature that seems compatible with the Brussels case is the one proposed by Deb et al. (2019). However, it is important to note that it requires a significant amount of accurate data on the distribution network of the geographical area under study.

Model Related Issues

The main limitations are related to the assumptions made.

For our proposed model, we decided to work with a coverage of the total demand in the region (one charging station for an average of 640 users: $\frac{M}{640}$) to really distinguish one station from another. This may result in one or more municipalities not having activated stations. An alternative could be to do demand coverage by region ($\frac{m_k}{640}$). This alternative would be part of a deployment plan where the intent is to activate at least one station for each municipality.

Another limitation has already been mentioned. It lies in the fact that the part of the objective function devoted to access costs is not strictly decreasing when a station is added. Although this may lead to similar results, future research can focus on reformulating the model to allow for better interpretability. For example, one can imagine a function that calculates the average access cost between all centers of the regions and the nearest (2, 3, 4, ...) open stations. Therefore, opening an additional station would decrease the average access cost.

Furthermore, one can imagine that an additional constraint can be added to the model. It would be a constraint that selected locations must be at least one or more kilometer away from each other. This would allow a better distribution of the selected stations over the search area.

Eventually, two limitations already mentioned could be waived in subsequent analysis. First, the model takes a global perspective while Brussel's 19 municipalities could in practice act independently and thereby propose local optimal locations. Second, the procedure disregards existing infrastructures. The introduction of a more sophisticated approach addressing both limitations will crucially rely on the availability of up-to-date private data on existing infrastructures and on the possibility to combine various relevant objective functions for each municipality with the necessary regional view.

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