Optimizing the Spatial Distribution of Battery Swapping Stations in the Urban Area Considering Urban Livability

Ximing Du
5612713
August 2023
MSc. Transport & Planning

TU Delft

Optimizing the Spatial Distribution of Battery Swapping Stations in the Urban Area Considering Urban Livability

Master thesis submitted to Delft University of Technology in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

in **Transport & Planning**

Faculty of Civil Engineering and eoscience

by

Ximing Du

Student number: 5612713

Graduation committee

Chair: Dr. ir. M. (Maaike) Snelder, SUM lab, Transport & Planning, TUD

Supervisor: Dr. ir. G. (Gonçalo) Correia, hEAT lab, Transport & Planning, TUD

Supervisor (advisor): ir. G.K (Koen) de Clercq, PhD candidate, Transport & Planning, TUD

Executive summary

An essential problem with electric vehicles (EVs) at present is the battery charging time. Even though fast-charging technology has been implemented in some areas, the charging time can still take up to thirty minutes, or even nearly an hour. To address this challenge, the concept of Battery Swapping Stations (BSS) has been proposed. The BSS infrastructure is expected to provide services to EVs similar to fuel stations for conventional vehicles, enabling EVs to quickly obtain a fully charged battery. Therefore, it is crucial to proactively plan for this infrastructure to serve EVs efficiently in the future. One critical aspect of this planning involves optimizing the locations of the BSS. While research has been conducted on developing optimization models to determine the best BSS locations within a city, with the objective of minimizing overall investment and operational costs of the BSS system or simultaneously minimizing travel time in the traffic network to optimize traffic assignment based on the best BSS locations, there remains a research gap. Existing optimization models fail to consider the concerns of urban residents in this problem. The negative impact of BSS on urban livability, such as the noise caused by charging piles and potential safety hazards from storing large battery inventories at the station, can lead to residents opposition to having BSS near their homes. Therefore, this concern is addressed in this thesis. A model has been developed to solve the optimal locating problem of BSS in the urban area, aiming to answer the following main research question:

Main research question: "How can an optimization model be constructed and applied to determine the best Battery Swapping Station locations in the urban traffic network, considering its impact on urban livability?"

To successfully address this question, the first step is to identify the stakeholders to be considered in the developed model. In total, three stakeholders are included: BSS system investors, urban residents, and BSS system users, who are EV drivers in the traffic network. The primary concern of BSS system investors is to minimize the construction costs of BSSs while ensuring that all battery swapping demands in the city are met. On the other hand, urban residents are concerned with minimizing the number of BSSs near their residences to maintain urban livability. Meanwhile, BSS system users aim to minimize their travel time during EV operation. However, it is essential to note that these concerns are interrelated and not mutually independent. As such, satisfying all stakeholders concer ns simultaneously can be challenging. By incorporating all three stakeholders in the model, it is reasonable to expect that a balanced and practical solution can be derived.

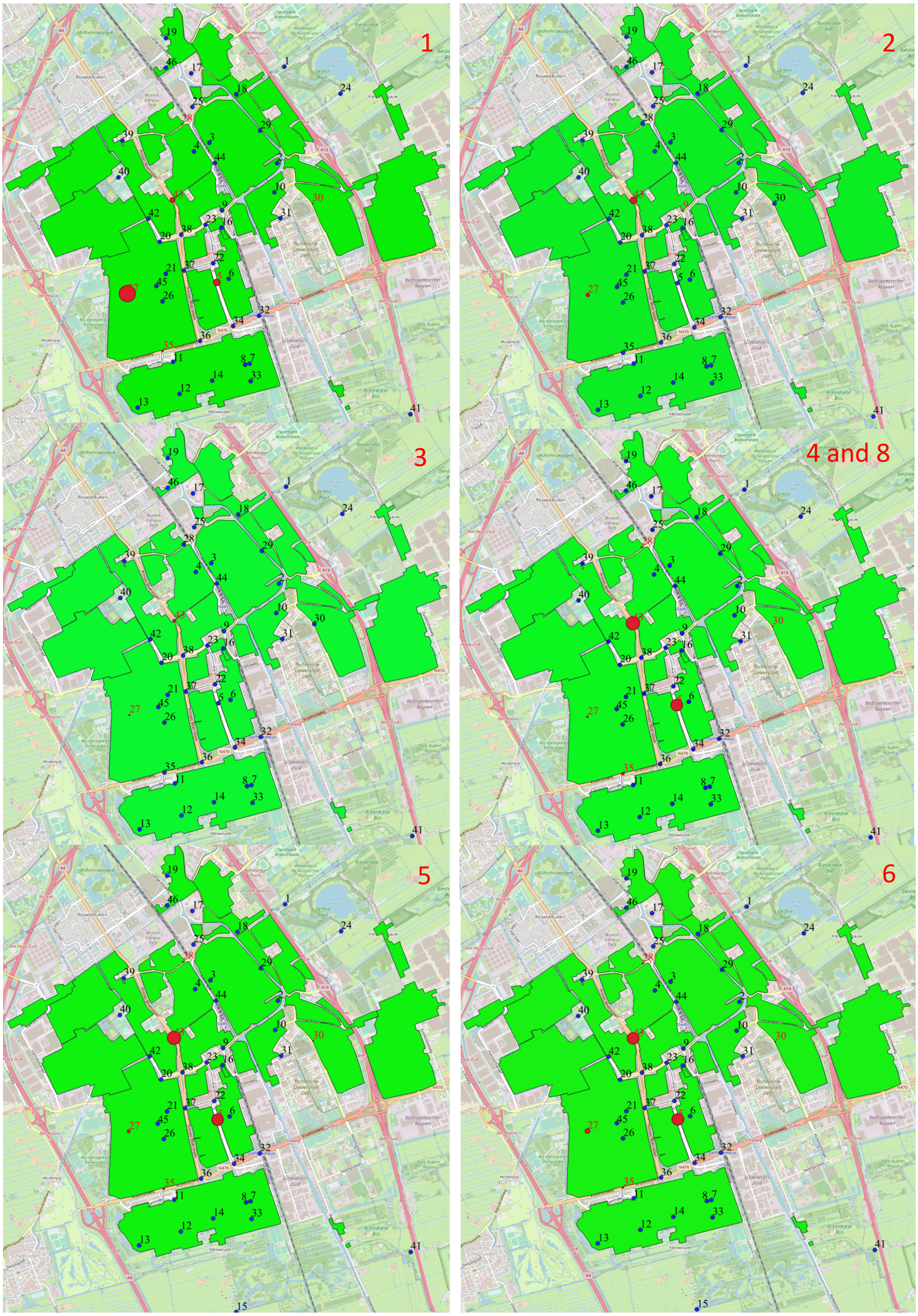
It is equally critical to consider how to evaluate and compare the concerns of stakeholders in the model. For the construction of a mathematical model, the aforementioned concerns must undergo quantitative evaluation. Moreover, it is essential that they are measured in the same unit to enable meaningful comparisons. In this thesis, both the concerns of urban residents and BSS system users are converted into monetary units for measurement, aligning them with the concern of BSS system investors. To account for urban residents reluctance to have BSS near their homes, the construction cost of a station in residential areas is set higher than in other parts of the city. The additional cost is estimated by calculating the expenses for constructing a sound

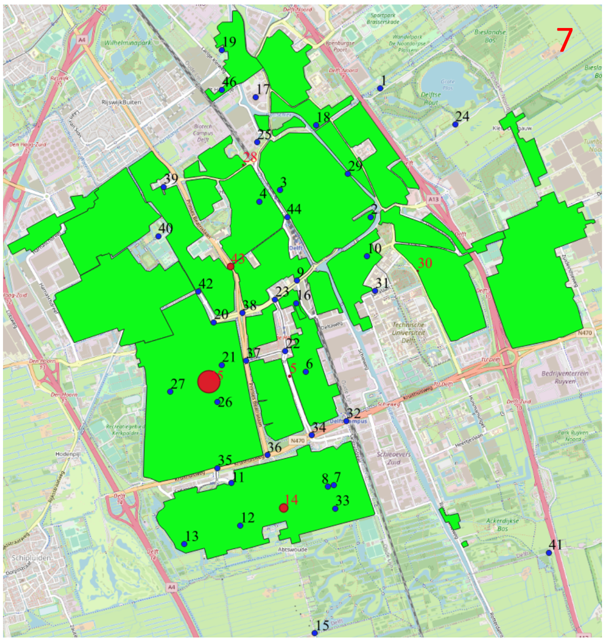
barrier and expanding the stations occupied area. Implementing a sound barrier can mitig ate the noise pollution caused by charging piles at the station, while a larger station area allows the operator to increase the distance between battery batches, reducing potential safety risks. The conversion of travel time into an economic indicator is relatively straightforward due to the mature and widespread use of the concept of Value of Time (VoT) in existing studies.

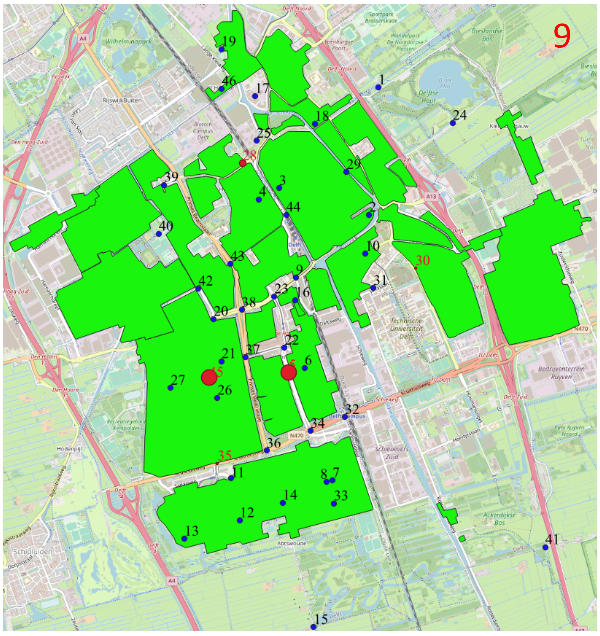
The unification of the evaluation for all three concerns enables the model to effectively capture trade-offs among them. This approach allows for the incorporation of different optimization preferences, meaning that the relative importance of each stakeholders concerns can be adjusted, making the model adaptable to various scenarios. In this regard, the models structure plays a vital role. To address the challenge of balancing multiple concerns in an optimization model, the existing literature was extensively reviewed, and several methods were explored, including bi-level optimization and multi-objective structures. After careful consideration, a linear structure with a single objective function was chosen. The objective function is formulated as a minimization function, where the concerns of all three stakeholders are organized in a linear manner. This enables the decision-maker to express their preferences by assigning specific weights to each term in the objective function. Moreover, this linear structure facilitates the incorporation of interactions among the three concerns during the optimization process and allows for efficient solution finding within a reasonable computation time.

Finally, the established model is applied to a real case - the city of Delft - to determine the optimal locations for constructing BSSs. Additionally, nine different scenarios that may be encountered in future planning are tested, providing valuable insights. Scenario 1, 2, and 3 focus on exploring the impact of increasing EV maximal traveling range on future optimal location planning. Scenario 4, 5, and 6 set three levels of station size limit in residential areas of the city to see how other factors in the optimization can be affected by this limit. Scenario 7 assigns a heavy weight to the travel time in the objective function of the model to obtain a better traffic network performance. Scenario 8 assigns a heavy weight to the construction cost of BSSs located in residential areas to reduce the station counts in this area. Scenario 9 increases the importance of economic expenditure on station construction over travel time in the city. The investigation reveals that an increase in the EVs traveling range leads to a reduction in daily battery swapping demands within the city, subsequently decreasing the number of required BSSs. Introducing a station size limit can alter vehicle station choices but may also result in more network detours and longer travel times. When the size limit is stringent, greater investments are necessary to accommodate larger or additional stations. Furthermore, conflicting objectives arise when considering preferences for improved travel time and reduced economic investment. Achieving a better travel time often requires increased economic investment, and vice versa. In one conducted experiment, implementing the preference for fewer stations in residential areas did not result in the expected decrease in station numbers. This outcome is attributed to the demand distribution in the city, which necessitates at least three stations in residential areas to fulfill all battery swapping needs.

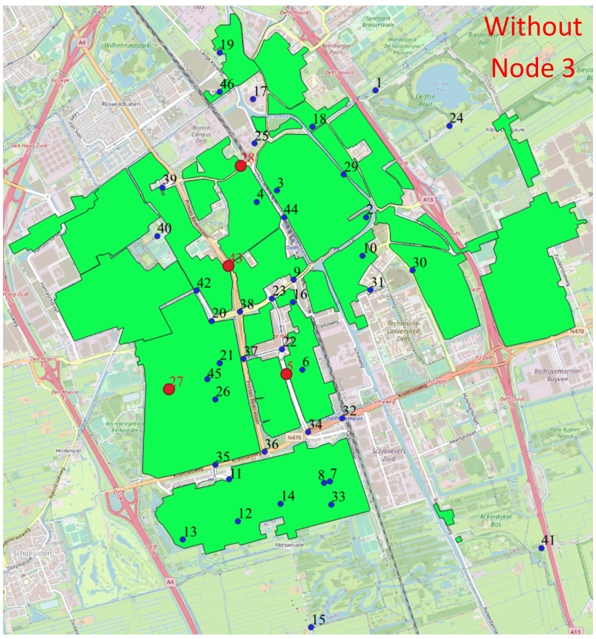
The following nine maps exhibit the optimal locations of BSSs in Delft under nine scenarios. Specific numerical results are exhibited and analyzed in Table 4.5.4 in Section 4.

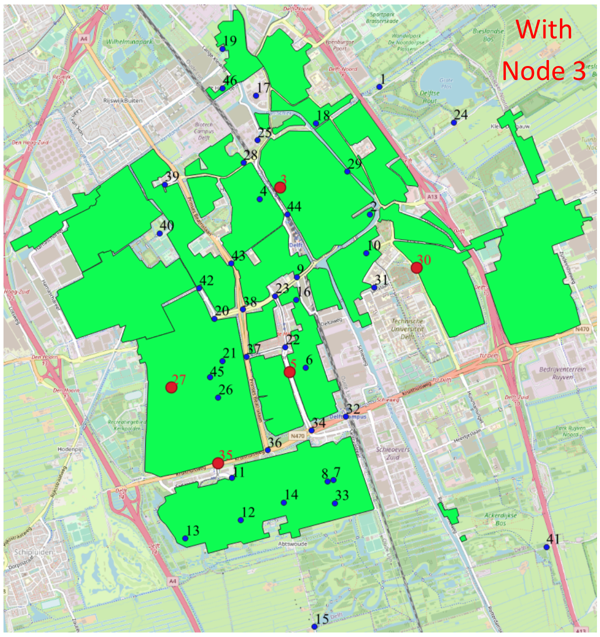

1
2
3
4 and 8
5
6





In addition to the analyses on potential impacts of various scenarios, specific suggestions are provided to the city of Delft on station location choice based on two possible conditions. One condition is to exclude all nodes that are considered unsuitable for building BSSs because of their surrounding physical environment. In this case, Node 5, Node 27, Node 28, and Node 43 are the four best locations to build BSSs and fulfill battery swapping demands in the city. Node 5 is on Pr. Beatrixlaan. Node 27 is in Buitenhof. Node 28 is on Kampveldweg. Node 43 is at the corner of the junction between Pr. Beatrixlaan and Westlandeweg. The other version is to ignore the bad construction condition at Node 3, which is located near Delft Station, found to be quite critical to fulfill battery swapping demands in surrounding areas and can lead to a good travel time in the city. In this case, the suggested locations for BSSs become Node 3, Node 5, Node 27, Node 30, and Node 35. Node 30 is close to the junction between Schoemakerstraat and Kloosterkade. Node 35 is at the junction between Kruithuisweg and Buitenhofdreef. The two versions of suggested locations are visualized in the following two maps.





This thesis research also offers valuable insights and inspiration for both planners and decision-makers. For planners, it highlights the importance of formulating BSS system location plans on a larger scale, encompassing regional networks that may span multiple cities and interconnected highway systems. Such a broader approach allows for achieving economies of scale during the investment stage and better capturing battery swapping behavior between cities. As for decision-makers, it is crucial to recognize the distinctions between different optimization strategies. The case study revealed instances where different scenarios led to the same solution, but this does not imply that the two scenarios (setting a station size limit in the residential area and implementing a preference for fewer stations in the residential area) are equivalent. When applying the model to other cities, employing these two strategies may yield significantly different solutions.

Regarding future research recommendations, it is advisable to enhance this model by incorporating the use of the BPR function for calculating link travel time instead of relying on a static network. Additionally, the application of queuing theory could provide a more accurate representation of the impact of vehicles station choices. Furthermore, the current model does not account for the dynamics of battery usage at each station. This can be improved by considering the service capacity of the stations in the model. Additionally, the thesis overlooks the charging behavior of EV drivers during the night. Including this aspect in future research on this topic can lead to more precise demand determination.

Preface

It has been a long journey since I arrived in Delft, the Netherlands on August 21, 2021. It is incredible to look back on the past two years here. Studying abroad is such a unique and attractive experience that I do not even realize that this journey will come to an end soon. I have been focusing on this master thesis for around eight months, from December 2022 to August 2023. The thesis generally concludes my two-year time as a master student at TU Delft. I would like to use this section to thank everyone who has supported and encouraged me throughout this thesis.

First of all, I would like to sincerely thank my three supervisors, Maaike, Gonçalo, and Koen. This was the first time I worked on a complete research question and completed a formal thesis. Thanks for your patience and guidance when I was facing difficulties or getting stuck during this thesis, which is invaluable. Every meeting with you gave me clearer direction and thinking, which enabled me to finish this thesis on time. Your encouraging words filled me with confidence and made me more motivated to push the progress. It was lucky for me to have this precious chance to work with you and learn from you. The words here are not enough to express all my appreciation. Thank you for everything!

Secondly, I want to thank my parents. You have been standing by me through every stage of my life. That was also the reason why I could grab the chance to study in Delft. Being able to have a video with you every week made my life in a foreign country feel less lonely. In the past two years, I got more aware that home is an eternal harbor for me to stay and rest. Now my life as a student will finally come to an end, and I hope my achievement so far can make you proud.

There is no way that I do not say thanks to my old friends here in Delft. Thank you, Tangzhe, Zhengliang, Xinran, Rui, Chen, Ke, and Haoyu. You have been accompanying me for five or six years since we first met at BJTU. I will never forget everything we have been through here. I could not have finished this thesis on time without your company. I cannot believe that we do not have much time to live and study together, meeting with each other every day. We may work in different cities in the future after we graduate, but I do hope we can reunite one day in Beijing. That means a lot to me.

Finally, there are some special thanks to my friends back in China. Thank you Tianshi, my dear sister. Our daily chatting and sharing in the past two years made me feel like you were here with me. I hope you can get your doctor's degree at Tsinghua University and find a satisfactory job soon. Thank you Haowen, Yuqing, and Meng. Your sharing often reminded me of our old days at BJTU. Hope to see you soon!

Two years here were like a fantastic long dream for me. Now it is time to wake up and keep moving forward. I am starting to look forward to seeing what will the next stage of my life be like!

Ximing

July 2023, at Delft, the Netherlands

Contents

Figure contents

Table contents

1. Introduction

With advancements in clean energy technology, there is a growing interest in applying clean energy across various industries as a replacement for traditional fossil fuels. The primary objective is to reduce and ultimately neutralize carbon emissions. Among the various categories of clean energy, electric power stands out as the most popular choice due to its widespread use in human society over an extended period (Dincer and Acar, 2015). Presently, the potential of electric power is being further explored, particularly in utilizing it to power vehicles by employing batteries instead of relying on thermal power generated from burning petroleum. This concept has been successfully realized to a significant extent, leading to the widespread production and introduction of electric vehicles (EVs) into markets worldwide, driven by the advancements in lithium battery technology (Hertzke et al., 2018).

Despite the rapid development of electric vehicles (EVs) in recent years, encompassing technological progress and increased market sales (Agrawal and Rajapatel, 2020), there are still significant challenges in their real-world application. One of the most prominent issues with EVs is related to charging. Despite the introduction of fast-charging technology, which has reduced charging times to less than an hour (Tu et al., 2019), the time required for charging an EV remains considerably longer compared to refueling a conventional vehicle, which typically takes only around five minutes, excluding waiting time at the station. Consequently, the charging issue significantly impacts the flexibility of drivers daily schedules. EV drivers must allocate specific periods for charging, during which they cannot engage in any other car trips. Furthermore, charging piles, the primary charging facilities for EVs, are predominantly situated near parking spaces (Zhang et al., 2020). In densely populated areas, the supply of parking spaces often fails to meet the demand. Consequently, EV drivers may struggle to find convenient charging spots near their homes or workplaces, posing a serious obstacle to the further development of EVs.

To address the aforementioned challenges, the concept of the "Battery Swapping Station" (BSS) was initially introduced by an Israeli company founded in 2007. Subsequently, many scholars worldwide have further studied and explored this concept. The BSS concept envisions a scenario where EVs can efficiently exchange depleted batteries for fully charged ones at the station, akin to the refueling process at conventional fuel stations. The BSS infrastructure would take charge of charging and storing the exchanged batteries (Wu, 2022). If this concept can be successfully realized in the future, it would alleviate concerns related to EV charging time and the availability of charging spaces. Presently, this idea has already been implemented for public transport vehicles, such as taxis and buses, in certain locations. The battery-swapping service locations are typically set at the depots of these vehicles. Buses, for instance, can conveniently swap batteries at their depots if the remaining power in the current battery is insufficient for the upcoming journey (Moon et al., 2020). However, it is crucial to highlight that these existing applications have no direct association with urban road traffic networks. The service is restricted to specific vehicles, and their operators do not need to strategize regarding demand scheduling or the placement of service locations within the traffic network. Addressing these precise challenges forms the core of developing public BSS systems. This research is built upon the assumption that the BSS concept can be effectively implemented in the future, encompassing these aspects within the urban road traffic network.

1.1 Problem definition and aim of the research

The main research question of this thesis is:

"How can an optimization model be constructed to determine the best Battery Swapping Station locations in the urban traffic network, considering its impact on urban livability?"

To date, various studies have been conducted to prepare for the future implementation of BSSs, covering a range of relevant topics, including the charging schedule problem, service policy problem, construction and planning problem, dispatching and routing problem, and power management problem (Wu, 2022). Determining the optimal locations for BSSs falls under the third category - the construction and planning problem. Several models have been developed with objectives such as minimizing the operation costs of stations or maximizing the overall profits of stations. These objectives primarily focus on the perspectives of station operators or investors. Additionally, more complex models incorporating multiple objectives or adopting a bi-level structure consider both economic costs and EV routing within the traffic network simultaneously, providing a more comprehensive optimization approach. However, there is currently a notable gap in the existing methodologies, as none of them adequately consider urban livability as a significant factor in the optimal location problem for BSSs. Presently, urban livability is a paramount concern for urban residents, with their quality of life profoundly influenced by the design and functionality of urban infrastructure (Martino, Girling, and Lu, 2021). As BSSs are poised to become an integral part of the future urban transportation landscape, they have the potential to impact the overall livability of urban environments. For example, the location of BSSs in the urban area will directly determine how much detour the EV driver will experience between the origin and the destination. Furthermore, the battery inventory in the BSS will bring a potential safety risk to its surrounding environment. Therefore, the absence of research considering this critical aspect leaves a significant gap in understanding how BSS location decisions can influence urban livability.

Building upon the identified research gap, the model developed in this research takes into account the interests of various stakeholders beyond system investors, including urban residents and system users (EV drivers). Urban residents are concerned about avoiding proximity to stations due to the noise generated by charging piles inside the station (Hu et al., 2023). On the other hand, system users desire a spatial distribution of stations within the traffic network that minimizes detours between their origins and destinations, ensuring minimal impact on travel time during battery swapping. Considering the concerns of these diverse stakeholders, the primary objective of this research is to formulate an optimization model capable of capturing trade-offs among their interests. By doing so, a balanced and optimal solution can be achieved. Moreover, the model aims to accommodate the decision-makers personal preferences by providing multiple optimal solutions instead of a single one. To ensure the established model exhibits these two essential characteristics, several sub-research questions are introduced in this thesis.

Sub-research question 1 *– "Which stakeholders should be considered in the optimization?"*

Sub-research question 2 *– "How to quantitatively evaluate all stakeholders' interests in the model?"*

Sub-research question 3 *– "How to make the model flexible for decision-makers so that they can apply personal preferences to the optimization?"*

Sub-research question 4 *– "How will the increasing traveling range of the EV influence optimal decision-making?"*

Sub-research question 5 *– "How will a station size limit in the residential area influence optimal decision-making?"*

Sub-research question 6 *– "How will different optimization preferences influence optimal decision-making?"*

The contents of this research will try to answer these two sub-questions. Figure 1.1.1 shows the conceptual framework of this research, which is also the guidance for developing the model.

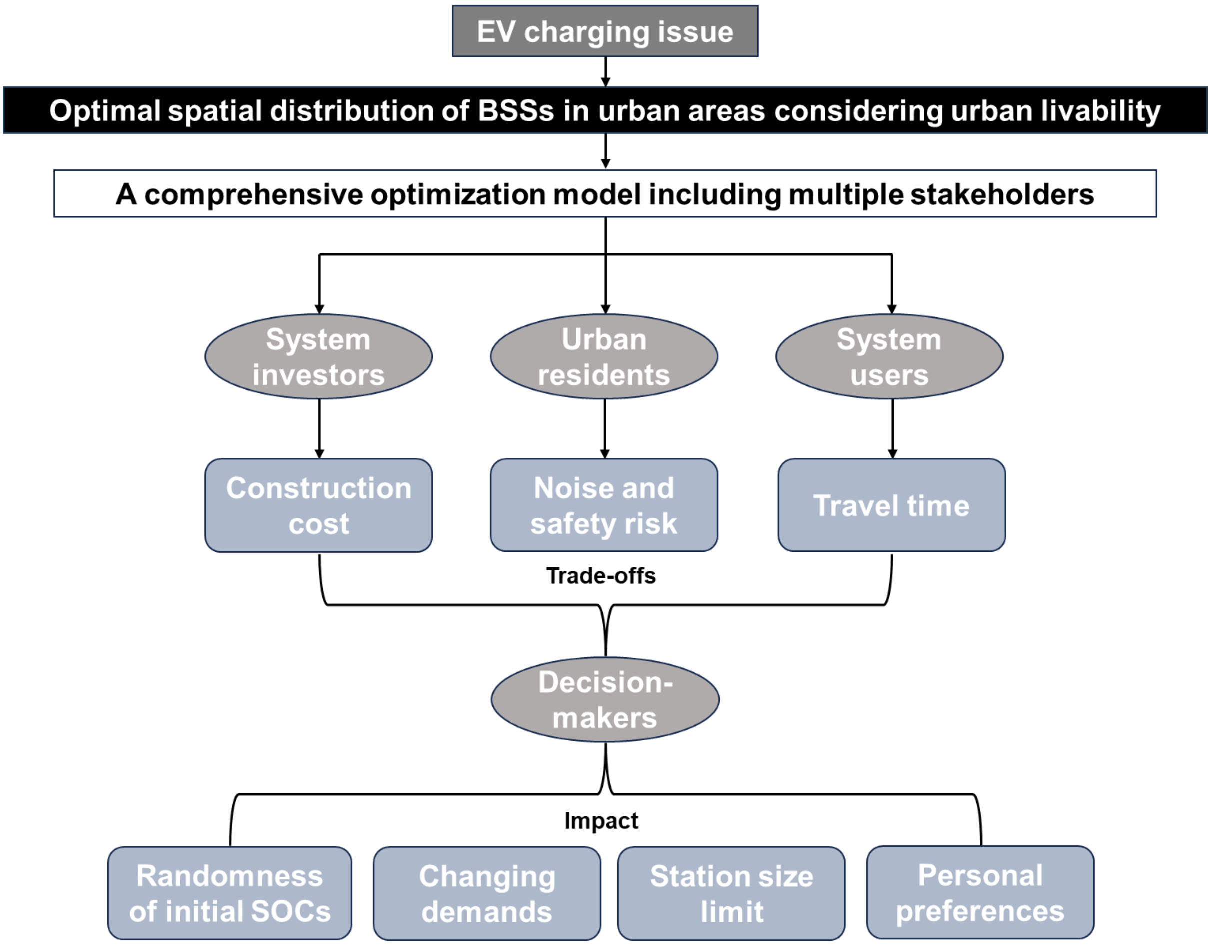


Figure 1.1.1 Conceptual framework of the research

1.2 Thesis organization

This section provides an overview of the thesis structure. Firstly, Section 2 presents the literature review, encompassing an analysis of existing literature on the current state of EV development, the envisioned organization of the BSS system, and methodologies for addressing the optimal locating problem. This review serves to address the first three sub-research questions. Section 3 details the development of the optimization model in this thesis, along with the corresponding fundamental assumptions. It provides specific answers to the first three sub-research questions. In Section 4, a real case study is conducted in the city of Delft, serving as an analysis and evaluation of the models performance, as well as its sensitivity to various scenarios. Sub-research questions 4, 5, and 6 find their answers in this section. Section 5 comprises the discussion part, where limitations of this thesis research are summarized. Finally, Section 6 serves as the conclusion of the entire research, explicitly providing answers to all proposed research questions. Figure 1.2.1 visually illustrates this structure.

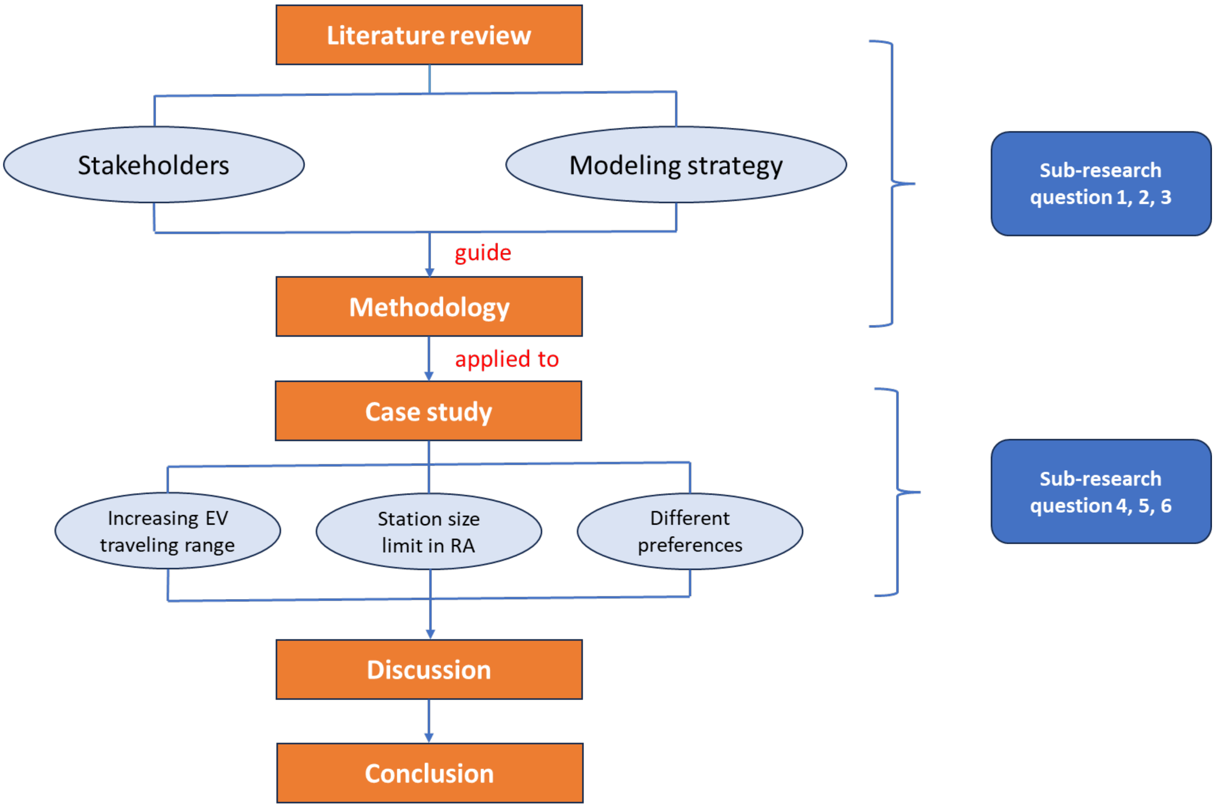


Figure 1.2.1 Thesis structure

2. Literature review

This section presents a comprehensive literature review focusing on existing research that addresses the optimal locating problem of the BSS. The review aims to identify which stakeholders have been considered in previous studies, how their interests and concerns are uniformly evaluated within the optimization process, and how the balance among these interests is achieved in the model. Additionally, this section briefly discusses various methodologies employed for optimal locating modeling strategies. Moreover, during the literature review, a knowledge gap will be identified, highlighting areas where current research falls short or lacks sufficient exploration.

2.1 Existing research on the BSS system

This subsection provides a concise introduction to the existing research on the BSS system, encompassing the envisioned organization of this infrastructure. It will also outline which stakeholders have been considered and modeled in the locating problem of the BSS system.

Wu (2022) conducted a comprehensive review of the state-of-the-art BSS literature and business models. Within his study, four potential organizational forms of the BSS system were identified and summarized. These included the single BSS system, the multiple BSSs system, the single BSS and single BCS system, and the multiple BSSs and BCSs system. Furthermore, the study compiled and analyzed existing research concerning the construction and planning problem of the BSS system, as presented in Table 2.1.1. This table clearly presents the assumed organizational forms of the BSS system, stakeholders involved, EV categories considered, and optimization objectives pursued in these studies.

Table 2.1.1 Existing research on the construction and planning problem of BSS (Wu, 2022)

Literature	***Mode***	***Decision maker***			***EV category***	***Objective***
		BSS operator	*EV Driver*	*Power Grid*		
Wang et al. (2020)	Multiple BSSs	√	×	×	Private EV	Max. Overall Profit
Hof, Schneider, and Goeke (2017)	Multiple BSSs	√	×	×	EV Taxi	Min. Construction cost Min. Routing cost
Zeng et al. (2019)	Multiple BSSs	√	×	×	EV Taxi	Min. Avg. Distance
Zheng et al. (2014)	Integrated BSS & BCS	√	×	×	EV Bus	Max. Net Present Value of the Project

Sultana et al. (2018)	Single BSS	×	×	√	Private EV	Min. Energy Loss & Max. Voltage Stability
Yang, Guo, and Zhang (2017)	Multiple BSSs & BCSs	√	×	×	Private EV	Max. Profit (i. Construction cost; ii. Operation cost; iii. Profit by Battery)
Liang, Cai, and Zou (2021)	Multiple BSSs	√	×	×	EV Taxi	Min. Load Difference Min. Emission Max. Financial Benefit
Sun et al. (2019)	Single BSS	√	×	×	Private EV	Min. Battery & Operating Cost Min. Charging Cost
This thesis	Multiple BSSs	√	√	Urban residents	Private EV	Min. overall "economic" cost

Based on the information presented in the above table, it becomes evident that existing research primarily focuses on three main stakeholders: the BSS operator, the EV driver, and the power grid. However, as previously highlighted, urban residents are conspicuously absent from these studies. Moreover, in most existing models, only one stakeholder is considered, leading to the neglect of the other two. In light of this limitation, this thesis aims to develop a comprehensive model that seeks to balance the interests of multiple stakeholders, ensuring that the final optimal solution incorporates the concerns of each relevant party. Additionally, this thesis will focus on a multiple BSSs system. The operation process of a multiple BSSs system is explained by the following diagram (Figure 2.1.1):

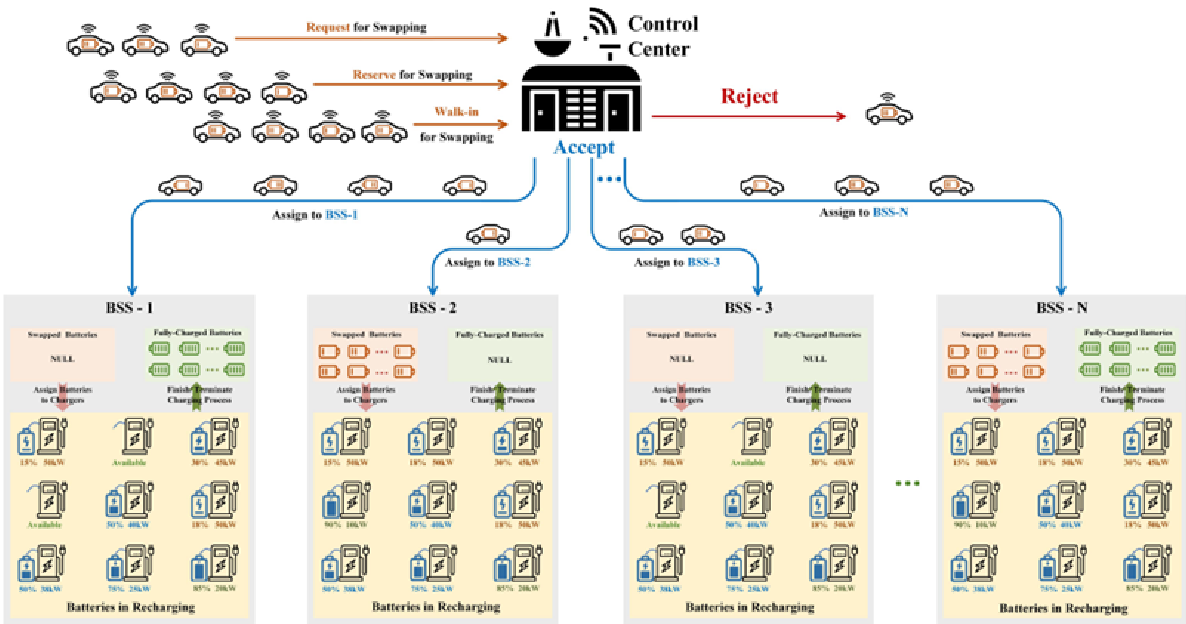


Figure 2.1.1 Operation process of a multiple BSSs system

The diagram above reveals the presence of a control center within this system, responsible for receiving service requests and efficiently assigning vehicles to different stations based on a specific objective, such as minimizing travel time. In this thesis, during the model development process, it will be assumed that EV drivers have access to information regarding the optimal station choice to achieve the shortest travel time between their origin and destination.

2.2 State-of-the-art: Modeling the optimal locating problem

As illustrated in subsection 2.1, the developed model in this thesis will encompass three stakeholders, ensuring that all their corresponding concerns are taken into account. Therefore, the primary focus of this subsection will be on existing modeling methodologies that effectively address multiple objectives in the optimization process.

Shao et al. (2022) introduced a mixed-integer linear programming (MILP) approach to ascertain the optimal planning of EV charging stations within transportation networks. Their study employed a bi-level model structure, with the upper-level optimizing the economic objective (minimizing overall costs), and the lower-level optimizing the travel time objective (minimizing total network travel time). By employing this modeling strategy, the two objectives were simultaneously optimized, effectively capturing the correlation between them.

Zang et al. (2018) also developed a bi-level planning model for EV charging stations in urban areas, taking into account the coupling relationship between charging stations and the travel routes of vehicles. One of the objectives in this model is to maximize the number of vehicles that can reach a station before their batteries run out of power, providing valuable insights for the constraint component of the developed model in this thesis. Another noteworthy aspect of this study is the sequential resolution of the proposed bi-level model, where the upper-level model dominates the lower-level model. Consequently, the lower-level objective had no impact on determining the optimal locating result of charging stations within the network.

Zhang et al. (2022) developed a multi-objective bi-level programming model to address the locating problem of EV charging stations. The upper-level model adopted a multi-objective structure encompassing economic expenditure and travel time considerations. Moreover, this study provided specific data on the solving time of the model, revealing that the time required for solving such a model could be considerable, especially when dealing with non-linear models.

Numerous scholars have explored the optimal locating problem of gas stations and charging stations from different perspectives. Li, Liu, and Wang (2022) delved into a collaborative optimization scheme, considering public charging infrastructure location and EV delivery route planning to minimize total costs. Wang and Wang (2010) introduced the constraint of nodal demand coverage, ensuring stations remained within reasonable distances to all nodes in the traffic network. Kim and Kuby (2011) addressed the optimal locating problem by focusing on travelers deviation from their original shortest paths due to refueling. They formulated a maximum covering approach, aiming to maximize the total covered refueling demand, assuming that travelers desire for refueling at a specific station decreases with the deviation from their original shortest paths. Lee et al. (2014) proposed a location problem for charging stations of EVs based on user equilibrium assignment, aiming to avoid congestion caused by improper station locations. Charging behavior of travelers was accounted for by assuming a probabilistic distribution of remaining fuel range at each origin node. Regarding the location problem of hydrogen refueling stations, this study provides valuable insights for determining battery swapping demands in a traffic network.

Existing studies have revealed that when addressing multiple objectives or concerns, the bi-level structure and multi-objective structure are the two most commonly employed methodologies for formulating the model. Additionally, researchers have observed that at times, a series of concerns can be amalgamated into a single objective function represented in a linear form. For instance, Shao et al. (2022) combined the economic cost of building new roads with the economic impact of network travel time in their upper-level model. However, this approach necessitates a unified measurement of diverse objectives, often achieved through the use of Value of Time (VoT) for converting time into economic costs. Each modeling methodology possesses its own advantages and disadvantages. Zang et al. (2018) demonstrated that a bi-level structure is effective in capturing interactions between two objectives. Nonetheless, caution must be exercised when setting constraints for both levels or when solving the model, as it can result in one level becoming over-constrained or dominated by the other level, leading to an imbalanced optimization. Additionally, solving a bi-level structure may be challenging and time-consuming, as reported by Zhang et al. (2022). While a multi-objective structure also captures correlations and interactions among objectives, it may lack flexibility for the decision-maker to apply specific preferences and obtain multiple alternative solutions, as noted by Chiandussi et al. (2012). On the other hand, incorporating all optimization concerns into a single objective function allows for containing their mutual interactions and offers ease of solving. However, such an approach demands a unified measurement for all factors to make them comparable to each other.

2.3 State-of-the-art: Modeling vehicles' station choices

Given that the EV driver will also play a role in the optimization process within this thesis, it becomes crucial to consider how to model station choices for EVs with battery swapping demands during their trips. This subsection will thoroughly examine existing literature on this specific topic.

Zang et al. (2018) further introduced a method for determining EVs station choices, employing the concept of "range anxiety," which correlates with the State-of-Charge (SOC) of the vehicle. The SOC indicates the remaining power in the vehicles battery and corresponds to the remaining distance that can be traveled by the vehicle. When the SOC falls below a certain level, the driver initiates the search for a station to charge the EV.

However, obtaining the EVs State -of-Charge (SOC) data is not a common practice at present. As an alternative, probability density functions are commonly employed to simulate the distribution of EVs SOC across the traffic network. Cao et al. (2012) utilized a normal distribution to directly simulate the percentage of vehicles remaining power, which proves to be particularly useful when other relevant information, such as the average daily travel distance of the vehicle and the number of days it has been traveled, is unavailable. Conversely, when such data is available, Akil, Dokur, and Bayindir (2022) proposed the use of a lognormal distribution to calculate the remaining distance for the vehicle.

Apart from the EVs SOC status, the choice of EVs station is closely related to its route selection. The process of choosing a station for battery swapping service involves the vehicle adhering to a mandatory regulation to pass through a specific node, necessitating a clear standard for selecting this node. Ferro et al. (2020) achieved this traffic assignment with the objective of reaching user equilibrium (UE) in the traffic network, utilizing the BPR function to accurately calculate the link travel time and incorporate the congestion effect. On the other hand, Shao et al. (2022) focused on minimizing individual travel time instead of achieving UE. Conversely, Li et al. (2023) bypassed traffic flow theory entirely and employed a probability density function to directly determine the number of vehicles that will choose specific stations within the network.

2.4 Research gap identification

Based on this literature review, it is evident that existing research on the construction and planning problem of the BSS system typically considers three stakeholders: the BSS operator, the EV driver, and the power grid. However, one crucial stakeholder, urban residents, is often omitted from this consideration. Urban residents hold significant concerns regarding the potential noise and safety risks associated with the BSS system. Therefore, when devising future plans for the construction of the BSS system, it is imperative not to overlook the willingness and concerns of urban residents. Neglecting their perspectives could lead to livability problems in the city once the plan is implemented.

Furthermore, existing models for planning the construction of the BSS system often make optimal decisions from the perspective of a single stakeholder, neglecting the importance of producing a more balanced solution that considers the concerns of multiple stakeholders. In reality, constructing the BSS system, much like planning for charging stations, requires taking into account the interests of various stakeholders. Maximizing the benefits for just one stakeholder is not a realistic approach and may lead to numerous complaints from other stakeholders.

Therefore, the main contribution of this research lies in the development of an approach that comprehensively considers multiple stakeholders simultaneously, including BSS system investors, urban residents, and EV drivers. The model takes into account the correlations and interactions among different stakeholders interests, ensuring a well-rounded representation. Furthermore, the developed model aims to assist infrastructure planners in arriving at a comprehensive decision while offering sufficient flexibility to incorporate their personal preferences in the optimal decision-making process. This approach enables the exploration of alternative solutions that reveal critical trade-offs among different stakeholders concerns.

3. Methodology

As previously introduced in Section 1, the research question of this thesis aims to establish a mathematical model that determines the optimal spatial distribution of BSSs in the urban area with a consideration of urban livability. The first sub-research question has been addressed in Section 2, where the model was developed to consider the interests and concerns of BSS system investors, urban residents, and EV drivers. In this section, sub-research questions 2 and 3 will be specifically addressed, focusing on finding an appropriate quantitative evaluation method for the stakeholders interests in the model. Additionally, the model will be designed to be flexible, allowing the decision-maker to apply different preferences to the optimization process, such as considering network travel time more important than the construction cost of stations, and vice versa.

3.1 Basic assumptions

All basic assumptions related to the model establishment will be introduced in this subsection, which are the basis of the model.

1) Firstly, the traffic network is assumed to be static, meaning that the travel time on each link is a fixed constant provided as input to the model. This constant remains the same for all time periods throughout the day. 2) Similarly, the waiting time for vehicles at a station is also set as a fixed constant. 3) The intra-node travel time is set to be 0, allowing vehicles to directly depart from a BSS if there is one located at their origin node. 4) Additionally, all vehicles with battery swapping demands are assumed to swap batteries only once during their trips, rather than multiple times. 5) Charging behavior will not be considered in this model; battery swapping is assumed to be the sole method for vehicles to obtain new power. 6) The battery dynamics at each station will be omitted in this model, with the assumption that vehicles need not be concerned about the service capacity of the station. 7) Finally, all EV drivers are assumed to have access to information about optimal station choices and will follow the recommended station assignments accordingly.

3.2 Data preparation

This subsection introduces the data requirements of the model, summarizing all necessary input datasets for the models implementation.

As the developed model operates on a traffic network, collecting some fundamental datasets is crucial. These datasets include the node set, the link set, and the link travel time set, as they provide essential mathematical features of the traffic network. Additionally, gathering trip information of vehicles is essential, as it constitutes one of the most deterministic elements for identifying optimal locations for BSSs.

Based on the above-mentioned information, the battery swapping demands can be determined. In this thesis, to judge if one vehicle will swap battery during its next trip, its initial SOC and the shortest path length between its origin and destination node will be compared. In mathematical words, assuming the shortest path length between vehicle i's origin and destination is sp_i, and the distance that can still be traveled by vehicle i is SOC_i. Then this vehicle will have battery swapping demand if:

$$sp_i > SOC_i \tag{1}$$

The vehicle will not swap the battery during its next trip if:

$$sp_i \leq SOC_i \tag{2}$$

To make this method more explicit, the following picture can be an auxiliary for the explanation:

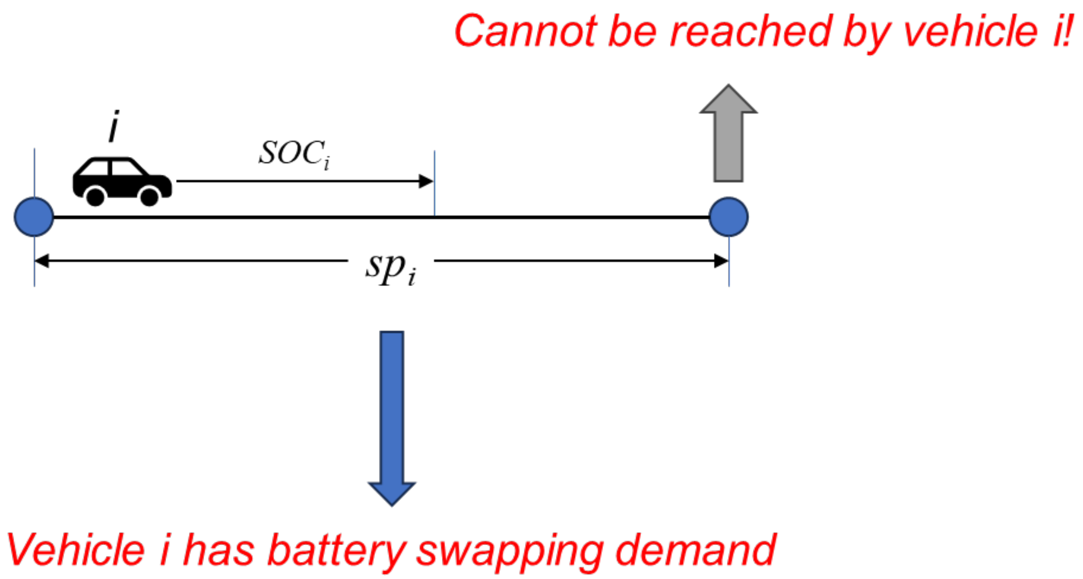


Figure 3.2.1 Battery swapping demand determination

From the above picture, it can be explicitly observed that the remaining power of vehicle i cannot support it to reach its destination. In this case, this vehicle will be considered to have battery swapping demands in this model.

Based on this criteria, two additional datasets need to be collected. The first dataset is the shortest path length set, which comprises the shortest path length for each origin-destination (OD) pair in the traffic network. It can be directly derived from the basic network data using the Dijkstra algorithm. The second dataset is the initial State of Charge (SOC) set for EVs. As mentioned in Subsection 2.3, this data is not widely available at present. Therefore, a probability density function can be employed to simulate the distribution of the initial SOC across all EVs in the city. In this thesis, a normal distribution is adopted, following the approach in Cao et al. (2012), and the probability density function is expressed as Equation (3):

$$f(S_0, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(S_0 - \mu)^2}{2\sigma^2}\right) \tag{3}$$

Where S_0 is the initial SOC (percentage) of a vehicle. μ and σ are parameters of the probability density function. μ takes the value of 0.5 and σ takes the value of 0.4. Equation (3) will be used to generate random initial SOC for each EV in the network in this model. The graph of this probability density function is shown in Figure 3.2.2:

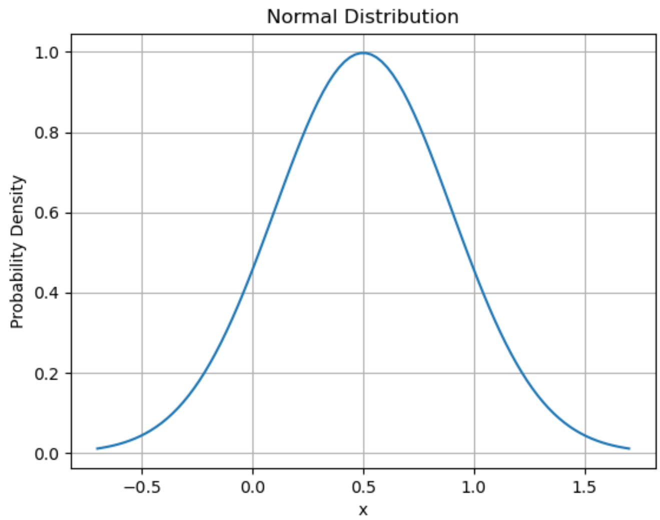


Figure 3.2.2 Probability density function curve

Then according to Equation (2), vehicles with a traveling range shorter than the shortest path lengths between their origins and destinations are considered to have battery swapping demands and will be put in the vehicle set as a part of model input.

However, S_0 in Function (3) is a percentage. It tells the SOC status on the basis of the comparison to the maximum range of the vehicle, so it does not tell specifically how far the distance that can still be traveled by the vehicle is. To realize this conversion from the percentage to the specific distance, the following formula can be applied:

$$SOC = R \times S_0 \tag{4}$$

Where *SOC* is the specific rest mileage that can be traveled by a vehicle.

With the datasets mentioned above, the determination of battery swapping demands can be completed. However, to perform all the necessary calculations in the model, some additional datasets are still required. These datasets include the fixed waiting time at stations, the Value of Time (VoT), and the construction cost of a station.

As the model operates on a static traffic network, vehicles without battery swapping demands will travel along the shortest paths between their origins and destinations, without impacting the optimization result. Consequently, the vehicle set will only include vehicles that require battery swapping during their next trips.

3.3 Model formulation

This subsection will comprehensively elucidate the quantitative evaluation of all stakeholders interests in the model and the models flexible structure enabling the application of various optimization preferences. It will present the mathematical formulation of the models o bjective function and constraints, accompanied by concise explanations of the implicit logic.

3.3.1 Model structure

In Subsection 2.2, three alternative modeling structures are illustrated to address multiple optimization objectives or concerns: bi-level structure, multi-objective structure, and a single objective function with multiple factors in a linear form. Each of these structures effectively captures correlations and interactions among different concerns. For this thesis, the single objective function approach is selected for the developed model, as it offers advantages over the other two structures. The multi-objective structure proves less convenient in applying diverse optimization preferences and providing multiple alternative solutions. On the other hand, the bi-level structures relatively long solving time duration renders it less efficient for the extensive testing required in the later case study. Thus, a single objective function that consolidates all stakeholders concerns emerges as the most suitable approach for this research. This structure necessitates the unified measurement of all stakeholders concerns. For instance, the interests of BSS system investors are naturally evaluated with a monetary unit, while EV drivers interests are a ssessed using a time unit. Urban residents concerns regarding noise and safety risk may employ various measurement units. To combine these diverse metrics into one cohesive objective function, a measurement conversion becomes essential.

The conversion method between time and money has reached a mature stage, with the widely adopted concept of Value of Time (VoT) in existing research. By incorporating VoT, this thesis calculates the economic impact of travel time, thus applying it to the developed model. Furthermore, to express urban residents concerns in economic terms, a "penalty" is considered for constructing stations in residential areas. This approach incentivizes investors to pay a higher price for stations located in residential areas compared to other parts of the city, naturally discouraging construction in such zones. This additional cost is estimated by considering the expenses of constructing sound barriers (for mitigating potential noise pollution) and extra land costs (for increasing the distance between battery batches stored in the station, thereby reducing safety risks). By employing this approach, all three stakeholders concerns are uniformly evaluated in monetary units, satisfying the requirement for a single objective function application. The final objective function will be a minimization function, as all three concerns included in the model represent "costs" for stakeholders, leading to negative effects. Thus, the optimization aims to minimize these negative impacts.

The model structure encompasses three components within the objective function. The first part represents the construction cost of stations located outside the residential area, while the second part reflects the construction cost of stations within residential zones. The last part quantifies the economic impact of the network travel time. By employing this structure, decision-makers can easily apply specific optimization preferences by adjusting the weight assigned to each part of the objective function. For instance, if the network travel time carries greater significance than station construction cost, a higher weight can be allocated to the travel time component in the objective function to prioritize this preference during optimization. Similarly, if urban residents strongly oppose BSSs in residential areas, the second part of the objective function can be given a higher weight to address this concern. Thus, this model structure offers decision-makers significant flexibility, providing an array of alternative solutions to address diverse scenarios.

3.3.2 Objective function

The previous subsection has determined the model structure. This subsection will introduce the mathematical formulation of the objective function on this basis.

The total cost for system investors is straightforward, encompassing the construction costs of stations both inside and outside residential areas. For stations situated outside residential zones, investors incur only the basic construction cost for each station. However, for stations constructed in residential areas, additional investments are required. Therefore, the total costs for investors can be expressed using the following functions:

$$Cost = \sum_{c} f_c y_c + \sum_{r} f_r y_r \tag{5}$$

$$f_r = f_{noise} + f_{safety} + f_c \tag{6}$$

Where, *Cost* is the total economic cost for investors. f_c is the basic construction cost per station. f_r is the total construction and investment cost of a station constructed in the residential area. y_c is a binary decision variable, which is 1 if a station is constructed at a (common) node *c*, located outside residential areas, and 0 otherwise. y_r is another binary decision variable, which is 1 if a station is constructed at node *r*, located in residential areas, and 0 otherwise. From Equation (6), it can be seen that f_r is the summation of the basic construction cost, the investment f_{noise} in noise mitigation measures, and the investment f_{safety} in safety enhancement measures.

In Equation (5), the second term $\sum_r f_r y_r$ is a unique term. It is a part of the system investors' costs, but it can also reflect one's emphasis degree to the livability level in residential areas because the investments in noise mitigation and safety enhancement are the input of the model. Besides, since f_r is the summation of the livability investments and the basic construction cost, the cost of a station constructed in the residential area must be more expensive than a station constructed in other areas. This naturally discourages construction in residential areas and follows an intuition that the number of stations in residential areas should be as small as possible in the real world.

From the above explanation, it can be understood that the total costs of system investors have already taken part of urban livability into consideration (the investments in living aspects). Another part that needs to be incorporated into the model is the network travel time. It has been explained that the network travel time is dependent on the spatial distribution of BSSs. Therefore, a shorter network travel time indicates a higher level of convenience for EV drivers under a certain spatial distribution. For the network travel time, the time unit can be easily converted into monetary units using *VoT*. Then the economic cost of the network travel time can be written as:

$$TC = VoT \cdot \sum_{i \in I} \sum_{n \in N} t_{i,n} x_{i,n} \tag{7}$$

$$t_{i,n} = to_{i,n} + td_{i,n} + w_n \tag{8}$$

Where TC is the equivalent economic cost of the network travel time. VoT is Value-of-Time. I is the vehicle set. N is the node set (containing all nodes). $t_{i,n}$ is the travel time of vehicle i choosing node n for its battery swapping. $x_{i,n}$ is another binary decision variable, which is 1 if a station constructed at node n is chosen by vehicle i for swapping the battery, otherwise, 0. From Equation (8), it can be observed that the travel time of a vehicle is divided into three parts: the first part is the travel time spent by the vehicle going from its origin to the station it chooses, denoted by $to_{i,n}$. The second part is the travel time spent by the vehicle going from the station it chooses to its destination, denoted by $td_{i,n}$. It is assumed that a vehicle will follow the shortest path from its origin to the station, and from the station to its destination. Therefore, given the shortest path length data of the network and the vehicle's OD pair, $to_{i,n}$ and $td_{i,n}$ are also known parameters that can be read from the shortest path length dataset no matter the vehicle chooses which station to pass through without any extra calculations. The last part is the dwell time of vehicle i in the station, denoted by w_n.

The station size is another crucial factor that must be incorporated into this model. It significantly influences the economic cost of a station since larger stations, catering to more vehicles daily, necessitate increased battery purchases, additional service facilities, and greater land rental. Consequently, these factors result in higher station costs. Thus, it is essential to account for the impact of the station size in the model.

Service demand stands as one of the most direct influencing factors determining the station size. The number of vehicles served by a station daily serves as a primary indicator for sizing the station appropriately. To establish specific station size classifications, a division into several levels is based on the service demand. Figure 3.2.4 illustrates the proposed classification method in this model:

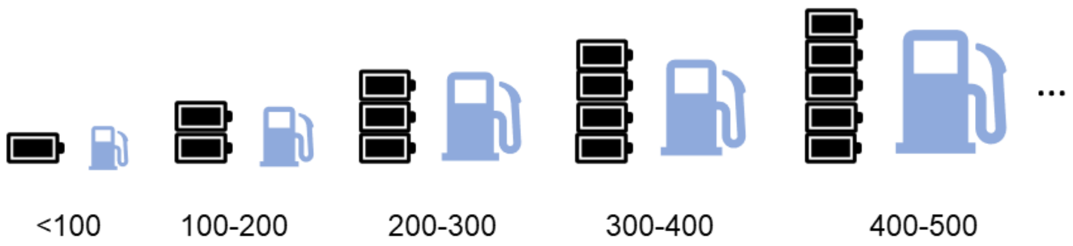


Figure 3.3.1 Station size classifications

The most basic station size is with a service demand less than 100 vehicles a day, which has a basic construction cost of f_c. Call this station size as "Level 1". If the station with the most basic size needs to serve 100 to 200 vehicle a day, then it needs to purchase more batteries and enlarge the station area (becomes a "Level 2" station). This can be seen as an upgradation of the station.

Then extra money f_s needs to be paid for this upgradation, and the total construction cost of this station becomes $f_c + f_s$. If the service demand increases a lot and this station needs to deal with 200 to 300 vehicles a day (a "Level 3" station after two times of upgradation), then the total money this station needs to pay for upgrading is $2 \times f_s$, and the total construction cost of such a station becomes $f_c + 2 \times f_s$. Therefore, f_s is the extra cost per upgradation of the station size. Let ε_n denote the number of times that a station is upgraded from the most basic size, and let s_n denote the service demand for the station located at node n. s_n can be calculated by:

$$s_n = \sum_{i \in I} x_{i,n}, \quad \forall n \in N \tag{9}$$

ε_n can be calculated by:

$$\varepsilon_n = \left\lfloor \frac{s_n}{100} \right\rfloor, \quad \forall n \in N \tag{10}$$

Equation (10) indicates that a station shall be upgraded for one time every 100 more vehicles choose it for having the battery swapping station. This is a simplification of the mathematical relationship between the station size and the corresponding construction cost because it is difficult to directly estimate the investment that a station needs to pay for serving one more vehicle in a day. Therefore, the station size classification scheme is applied here and a fixed construction cost is set for each size level.

Then, the total economic costs that will be burdened by the system investors becomes:

$$Cost = \sum_{c \in C} (f_c + \varepsilon_c f_s) y_c + \sum_{r \in R} (f_r + \varepsilon_r f_s) y_r \tag{11}$$

In the final objective function, directly summing the economic cost and the economic effect of travel time is not appropriate due to their different time scales. Investing in the construction of BSSs requires immediate spending, whereas the stations operate for many years, serving battery swapping demands daily during their lifespan. Conversely, the travel time is assessed on a daily basis, not spanning over years. To establish a consistent final objective function, both aspects should be measured on the same time scale. Since the travel time is measured daily, the economic cost should be similarly calculated to represent the average daily expenditure investors would spend. Let T denote the lifespan of the BSS; accordingly, the average daily expenditure for construction can be calculated as follows:

$$Daily\ cost = (\sum_{c \in C} (f_c + \varepsilon_c f_s) y_c + \sum_{r \in R} (f_r + \varepsilon_r f_s) y_r)/T \tag{12}$$

Then the final objective function of the model will be the combination of system investors' daily costs and network travel time cost, written as Equation (13):

$$\min Z_1 = (\sum_{c\in C}(f_c + \varepsilon_c f_s)y_c + \sum_{r\in R}(f_r + \varepsilon_r f_s)y_r)/T + VoT \cdot \sum_{i\in I}\sum_{n\in N} t_{i,n}x_{i,n} \quad (13)$$

Equation (13) inherently assigns equal weights to the construction and investment costs and network travel time cost since the two parts are directly summed up to build the objective function. In practice, this function offers significant flexibility in assigning weights. For instance, if the decision-maker prioritizes economic cost over guaranteeing an optimal traffic network performance, they can place a heavier weight on the first two terms of the function compared to the network travel time cost. Conversely, if emphasizing minimal network travel time is essential, they can assign a higher weight to the travel time component. Moreover, this weight can vary between the total construction cost of stations outside residential areas and the total construction and investment costs of stations in residential areas. To discourage station construction in residential areas, a heavy weight can be placed on the second term of the function. Consequently, designing different weighting strategies allows for the exploration of diverse optimization ideas. Meanwhile, the decision-maker retains clarity regarding the specific cost and gain associated with each term, which facilitates determining preferences.

3.3.3 Constraints

This subsection will introduce all constraints of the model. The first two constraints are to calculate the service demand for the station and determine the station size, which have already been proposed before (Equation (9) and Equation (10)).

The third constraint of the model is to regulate vehicles' station choices. Since the model allocates stations at a set of nodes, vehicles' station choices are essentially choosing a certain node to pass in this model. Therefore, a problem appears: vehicles might choose a node to pass at which no station is constructed. In this case, vehicles' routes become irrational, and the solution is meaningless. To deal with this problem, the following two inequalities must be written:

$$y_c \geq x_{i,c} \quad \forall c \in C, i \in I \quad (14)$$

$$y_r \geq x_{i,r} \quad \forall r \in R, i \in I \quad (15)$$

Constraints (13) and (14) regulate that a vehicle can only choose to pass a node at which a BSS is really constructed during its trip. Where *C* is the common node set. *R* is the residential node set. *I* is the vehicle set.

The fourth constraint is still about vehicles' station choices. In order to avoid the situation that a vehicle does not choose any station to swap battery, or it chooses multiple stations to swap battery, there must be a constraint to limit the number of stations a vehicle can choose, written as the following equation:

$$\sum_{n \in N} x_{i,n} = 1 \quad \forall i \in I \tag{16}$$

Constraint (15) regulates that for any vehicle, it must choose and can only choose one station to swap the battery. Where *N* is the node set (containing all nodes in the network). And *n* is a node in *N*.

The last constraint is the valuing range of binary decision variables, written as the following:

$$x_{i,n} \in \{0, 1\} \;\; \forall i \in I, n \in N \tag{17}$$

$$y_n \in \{0, 1\} \;\; \forall n \in N \tag{18}$$

3.3.4 Overall formulation of the model

Table 3.3.1 Notations and corresponding descriptions

Notation	***Description***
Sets	
I	Set of vehicles
N	Set of all nodes in the network
C	Set of nodes located outside residential areas
R	Set of nodes located in residential areas
Indices	
i	Vehicle in vehicle set I
n	Node in the whole network
c	Node outside the residential area
r	Node in the residential area
Parameters	
f_c	Fixed construction cost of a BSS at node c
f_r	Construction cost of a BSS at node r
$t_{i,n}$	Total time spent of vehicle i choosing station n for having service

VoT	Value of Time, a constant
$to_{i,n}$	Time spent by vehicle *i* going from its origin node to BSS located at node *n*
$td_{i,n}$	Time spent by vehicle *i* going from BSS located at node *n* to its destination node
f_{noise}	Extra investment for mitigating noise pollution in residential areas
f_{safety}	Extra investment for enhancing safety levels in residential areas
s_n	Service demand for the station constructed at node *n*
ε_n	The level of station size at node *n*
SOC_i	State-of-charge of vehicle *i* when it departs from its origin, denoted by the distance that can be traveled by an EV before swapping battery
w_n	Average time spent at BSS located at node *n*
Decision variables	
y_c	Equals 1 if a BSS is constructed at node *c* and 0 otherwise
y_r	Equals 1 if a BSS is constructed at node *r* and 0 otherwise
$x_{i,n}$	Equals to 1 if vehicle *i* chooses BSS located at node *n* for having service

$$\min Z_1 = (\sum_{c \in C} (f_c + \varepsilon_c f_s) y_c + \sum_{r \in R} (f_r + \varepsilon_r f_s) y_r)/T + VoT \cdot \sum_{i \in I} \sum_{n \in N} t_{i,n} x_{i,n} \tag{13}$$

s.t.

$$s_n = \sum_{i \in I} x_{i,n}, \quad \forall n \in N \tag{9}$$

$$\varepsilon_n = \left\lfloor \frac{s_n}{100} \right\rfloor, \quad \forall n \in N \tag{10}$$

$$y_c \geq x_{i,c} \quad \forall c \in C, i \in I \tag{14}$$

$$y_r \geq x_{i,r} \quad \forall r \in R, i \in I \tag{15}$$

$$\sum_{n \in N} x_{i,n} = 1 \quad \forall i \in I \tag{16}$$

$$x_{i,n} \in \{0,1\} \ \forall i \in I, n \in N \tag{17}$$

$$y_n \in \{0,1\} \ \forall n \in N \tag{18}$$

3.4 Model test

Prior to applying the model in a real case, it is essential to evaluate its performance in a virtual environment to ensure it produces rational results that align with intuition and expectations. To conduct this test, a toy traffic network is created.

3.4.1 Toy network structure

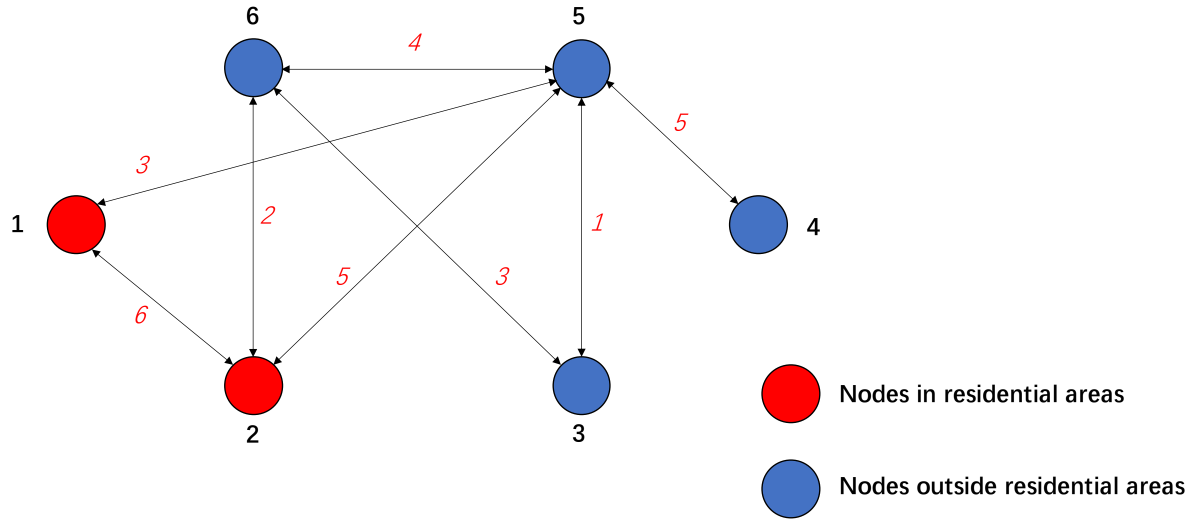


Figure 3.4.1 Structure of the toy network

The prototype network comprises 6 nodes connected by weighted links, with the link weight data representing link travel time. Among the 6 nodes, Node 1 and Node 2 are situated in the residential area, while the remaining four nodes (Node 4, 5, 6, 7) are located outside the residential area. The network structure is visually presented in Figure 3.4.1.

3.4.2 Data input

The models inputs can be categorized into two types: input datasets, comprising the node set, link set, link weight set, and trip demand matrix, and parameters, including the basic construction cost of a BSS, additional investments in stations constructed in residential areas, weights assigned to each part of the objective function, initial State of Charge (SOC) of each vehicle, dwell time at a station, Value of Time (VoT), and intra-node travel time. These inputs are summarized in Table 3.4.1:

Table 3.4.1 Data input of the model

Dataset	***Parameter***

Node set	Basic construction cost of a station
Link set	Extra livability investments of a station
Link weight set	Weight on each term in the objective function
OD matrix (demand matrix)	Initial SOC of each vehicle
Vehicle OD set	Time spent at a station
	VoT
	Intra-node travel time

The node set, link set, link weight set, and demand matrix, along with the derived shortest path length set, are presented in Appendix A. The test involves simulating a total of 1271 vehicles, all with battery swapping demands. The corresponding OD pair of each vehicle is sequentially selected from the trip demand matrix. For this test, the basic construction cost of a common station is set to 1000 euros. While this may seem irrational as the real construction cost is considerably higher, this choice is made to prevent the network travel time (multiplied by VoT) from becoming too insignificant compared to the construction cost. This ensures that the construction cost does not dominate over the network travel time in the optimization process. The same principle is applied when determining investments in noise mitigation and safety enhancement measures. Additionally, the unit upgradation price for the station is set at 100 euros, and the initial weight assigned to each term in the objective function is 1. The weight distribution will vary in different scenarios to simulate diverse optimization preferences and strategies. The value of VoT is derived from existing literature, specifically Goldszmidt et al.s research (2020), which reported VoT as 19 euros per hour (0.3 euros/min).

3.4.3 Model output

As per the model formulation, the models output will encompass the following key results: optimal station locations, network travel time, travel time of each vehicle, total livability gain, station choice of each vehicle, and service demand for each station.

Moreover, the network data solely comprises the node set, link set, and link weight set, lacking information about the shortest path between arbitrary node pairs. Consequently, prior to model operation and calculation of the total network travel time, it is necessary to preprocess the network data to determine the shortest path length for every pair of nodes in the network.

3.4.4 Scenario settings

In this test, three scenarios are experimented to simulate different optimization preferences and evaluate if the output aligns with expectations. The weights used in these scenarios are chosen to explore specific optimization directions, aiming to generate diverse solutions for subsequent analysis. The results obtained from these scenarios provide preliminary insights into the models characteristics and anticipate potential situations for later case studies and analysis. It is important to note that the weights used in this test do not represent precise strategies. For instance, the scenarios constructed here do not simulate a specific strategy where the decision maker believes network performance (network travel time in this model) is twice as important as economic costs.

Scenario 1 represents the natural optimization strategy, where the weight on all three terms in the objective function is set to 1. Additionally, investments in noise mitigation and safety enhancement are considered. For noise mitigation, an investment of 300 euros is allocated, while safety enhancement receives an investment of 200 euros. As previously explained, these are irrational numbers used to prevent the dominance of construction and investment costs in this test. Consequently, the total cost of constructing a BSS in the residential area amounts to 1500 euros in this scenario.

Scenario 2 represents an extreme optimization direction where the construction cost of stations outside residential areas is of minimal concern, while the costs of stations in residential areas and the network travel time remain important. To achieve this, the weight on the construction cost of stations outside residential areas is set to be 0.001, while the weights on the other two terms remain the same as in Scenario 1. All other settings are identical to those in Scenario 1. Consequently, it is anticipated that the number of stations outside residential areas will increase, and the network travel time will decrease compared to Scenario 1.

Scenario 3 represents another extreme optimization approach that seeks to minimize the number of stations (or create the smallest station size) in the residential area. For this purpose, the weight on the construction cost of stations in the residential area is set to 1000. All other settings remain the same as in Scenario 1. Consequently, it is expected that Scenario 3 will result in a reduced number of stations in the residential area due to the significantly higher cost per station.

To make these scenario settings clear and explicit, Table 3.3.2 summarizes the settings for each scenario:

Table 3.4.2 Scenario settings in the model test

Scenario	***Weights on three terms in the objective function***	***Noise investment***	***Safety investment***	***Total cost per station in the residential area***
1	[1, 1, 1]	300	200	1500
2	[0.001, 1, 1]	300	200	1500
3	[1, 1000, 1]	300	200	1500

3.4.5 Test results

Scenario 1 begins to take urban livability factors into consideration. There are in total 5 stations are constructed in the network, at Node 1, 4, 5, 6. The service demands for these stations are 301, 295, 279, 396, respectively. The total travel time in the network is 9903 minutes. The total livability gain for urban residents is 3792 euros.

Scenario 2 decreases the weight on the cost of stations outside the residential area compared to Scenario 1. Then the optimal location result has one station more than Scenario 1, so in total, five stations are constructed in Scenario 2, at Node 1, 3, 4, 5, 6. The corresponding service demands are 301, 23, 295, 256, and 396. The network travel time is 9898 minutes. The livability gain for urban residents is 3794 euros. Although the change is not big compared to Scenario 1, but the change follows the expectation illustrated in Subsection 3.3.4.

Scenario 3 increases the investments in urban livability. However, the entire output is exactly the same as Scenario 1, thus contradicts to the intuition inference mentioned in Subsection 3.3.4. The reason for this will be analyzed in 3.3.6.

To summarize the test results, Table 3.3.3 is exhibited below:

Table 3.4.3 Test results of four scenarios

Scenario	***Location result***	***Service demand***	***Network travel time (min)***	***Station level***
1	[1, 0, 0, 1, 1, 1]	[100, 0, 0, 100, 800, 271]	9903	[1, 0, 0, 1, 8, 2]
2	[1, 0, 1, 1, 1, 1]	[100, 0, 409, 299, 337, 126]	9898	[1, 0, 4, 2, 3, 1]
3	[1, 0, 0, 1, 1, 1]	[100, 0, 0, 100, 800, 271]	9903	[1, 0, 0, 1, 8, 2]

3.4.6 Result analyses

Although there are only three scenarios tested, adequate information can be inferred from their results. This subsection will conduct a simple qualitative analysis of the results of three scenarios.

1) A comparison between Scenario 1 and 2 reveals that an additional station is constructed at Node 3 in Scenario 2. However, the network travel time in Scenario 2 is merely 5 minutes less (9898 minutes) than in Scenario 1. Consequently, constructing a new station at Node 3 has minimal impact on improving network performance. Furthermore, Scenario 2 exhibits a more widespread distribution of vehicles battery swapping demands compared to Scenario 1. This is particularly evident in the service demands for stations outside the residential area, where the sizes of stations are similar in Scenario 2. In cases where the construction cost of a station is of great significance to the decision maker, they tend to construct larger stations at specific locations in the network to avoid building multiple stations in various places. This explains why Scenario 1 includes a station constructed at Node 5 with a size level of 8. In contrast, Scenario 2 features demand distribution across various locations as the construction cost becomes less influential. These results demonstrate that different optimization strategies not only affect the number of stations but also impact the size of the station.

2) Scenario 3 has exactly the same result as Scenario 1. At first glance, this outcome may appear counterintuitive, given the significantly higher weight assigned to the construction cost of stations in the residential area. One might expect the station constructed at Node 1 in Scenario

1 to be removed in Scenario 3 to lower the objective value. However, this result can be explained by a constraint in the model (Constraint (15)) that dictates each vehicle must select and can only select a station for battery swapping service, ensuring that all demands are met through the spatial distribution of stations. As a result, a station at Node 1 must exist to cater to certain vehicles service demands, enabling them to reach a station before their batteries run out of power. This observation points to the existence of a boundary value for discouraging station construction in residential areas. In other words, there can be a minimum value for the number or size of stations in the residential area. Once this minimum value is reached, the number of stations in residential areas will no longer decrease, regardless of how heavy the weight is.

In conclusion, the testing scenarios have revealed several intriguing insights. For instance, reluctantly adding a new station in the network may have no discernible impact, leading to negligible improvement in the traffic network and urban residents livability gain . Moreover, excessive investments in stations in residential areas might not yield significant benefits, as the number of stations will not decrease once a certain boundary condition is reached, given that all vehicles service demands must be met. Consequ ently, additional livability investments may not translate to substantial progress in the traffic network performance. Notably, the prototype network used for testing is relatively small, with only six nodes and 1200 vehicles. In reality, traffic networks are significantly larger and more complex, presenting a greater array of possibilities in the final optimization results. A larger network size offers the model increased flexibility to discover optimal solutions. Detailed exploration of this models chara cteristics will be undertaken in the forthcoming case study in Section 4.

4. Real case study: the city of Delft

In this section, the optimization model established in Section 3 will be applied to a real traffic network in Delft, the Netherlands. The aim is to examine the impacts of various factors on the optimization results through a series of experimental scenarios. These factors include the randomness of EVs initial SOC, EVs maximum traveling range, station size limit, decision - makers preferences f or a shorter network travel time, fewer stations in the residential area, and reduced economic cost for constructing stations. Consequently, Sub-research questions 4, 5, and 6 will be addressed in this section.

This section will comprehensively evaluate the performance of the established model to identify its strengths and weaknesses. Based on the experiment results, practical BSS location planning advice for Delft will be provided. Additionally, the outcomes of the experiments conducted in various scenarios will serve as valuable references for all decision-makers faced with the location problem, considering the interests of different stakeholders.

This section is structured into six parts. Subsection 4.1 introduces the dataset used for this case study, including its advantages and disadvantages. Subsection 4.2 explains the data processing methodology and the determination of battery swapping demands in the Delft network. Subsection 4.3 presents the settings of different scenarios in this case study and their respective purposes. Additionally, key parameter inputs of the model will be exhibited in this subsection. Subsection 4.4 proposes several Key Performance Indicators (KPIs) to comprehensively evaluate the models performance un der different scenarios, providing a comprehensive analysis of all aspects related to the locating problem. Subsection 4.5 exhibits the results obtained from each scenario, which will be quantitatively analyzed based on the previously proposed KPIs to reveal the impacts of various factors. The final subsection will provide an overall review of this case study.

4.1 Dataset introduction

The dataset used for this case study is the one used in Correia, G.H., van Arem, B. (2016) to explore the impacts of self-driving vehicles on urban mobility. This is a highly comprehensive dataset that includes travel data, node coordinates, network data, and public transport data in Delft City, The Netherlands. In travel data, 3432 trips are collected. In fact, these trips are concentrated from a complete trip set (so proxies of many households). Each trip in this dataset can be expanded to 20 households in this city. Therefore, the actual total number of trips is 68640. Corresponding data to each trip includes the origin node and the destination node, the household number, the number of members in a household, the number of trips of the identified member, the number of automobiles of the family, the departure time of the trip, the arrival time of the trip, an expansion coefficient (can multiply for this family to yield the real number of families), the number of the day in which the data was collected, the year in which the data was collected, the weekday in which the data was collected, departure address of the trip, arrival address of the trip, trip purpose, the traffic mode used for the trip, the number of stages in the trip, approximate trip distance, occupation of the car, approximate original (expected) travel

Figure 4.1.1 Satellite map of Delft network (source: Correia, G.H., van Arem, B. (2016))

time, and the original expansion of the survey. For the departure address and arrival address of the trip, they are both categorized into 16 types. These trip addresses include home, work, relatives/friends' home, education, shopping, personal care, sport/hobby, other leisure, a ride or a walk, business, transport is a profession, carrying persons, carrying goods, going along with a companion, other, and missing data. 23 traffic modes are identified in this dataset, including walking, bicycle driver, bicycle passenger, light moped ("snorfiets"), moped ("bromfiets"), motorcycle, car driver, car passenger, train/light rail/tram, underground, bus public transport, taxi, buggy, skates/skeelers, transport mode for disabled, tractor, delivery van, truck, coach, private bus transport, ferry, airplane, and other modes. The node coordinates give the X and Y coordinates of each node, which is useful when doing the visualization in the network. The network data contains adequate information as well. It provides the starting node and end node of each link, the ID of the link, the free-flow travel time (in minutes) of the link, the maximum travel time (in minutes) of the link, driving speed (in km/h) of the link, the capacity (number of vehicles per hour) of the link, and the length (in meters) of the link. With the network dataset, the traffic network of Delft can be built. The last subset is the public transport dataset, which depicts the public transport network in Delft, with starting and ending nodes, and corresponding distances between the two nodes. This subset will not be used for this case study because the battery swapping demands of buses are not considered in this model. In reality, it is more likely that electric buses will swap the battery at their depots instead of at public BSSs. The satellite map of the Delft network is shown in Figure 4.1.1, with all nodes' positions on it.

There are several critical advantages of this dataset are concluded here. 1) The dataset encompasses entire day-long trips, enabling the capture of all vehicle patterns throughout the day. This comprehensive coverage leads to more robust and well-rounded optimization results. The diverse behaviors of vehicles traveling between home and work, such as avoiding shops and supermarkets during the morning commute but potentially making stops during the evening return journey, highlight the necessity of accounting for the full range of trip types. Using a dataset limited to either morning or evening peak trips could yield a one-sided optimization outcome. Furthermore, the datasets inclusivity extends beyond peak hours, accommodating battery swap demands that may arise during other time periods, and contributing to a holistic solution. 2) The dataset furnishes two distinct link travel times: the free-flow and maximum link travel times. Given that this model operates on a static network, where link travel times remain constant and fixed, neither the free-flow nor the maximum travel time alone is suitable due to their inherent biases. In a dynamic traffic network, congestion and free-flow conditions vary throughout the day. To overcome this, a more balanced approach is suggested by combining these two potential link travel times, such as averaging them or calculating a weighted sum average. The dataset conveniently permits such amalgamation. 3) Notably, the dataset explicitly differentiates between various traffic modes. Earlier sections have outlined the collection of traffic mode choices for each trip, encompassing several modes of travel. This distinction proves invaluable for identifying potential electric vehicle (EV) trips from the dataset. By solely knowing the origin-destination (O-D) information without insight into the chosen mode of travel, it becomes challenging to ascertain the proportion of trips within the O-D matrix that involve cars, trucks, coaches, and so forth. The significance of this distinction is exemplified by the ability to classify walking trips as EV trips, avoiding skewed battery swap demand estimations in the network. Through a well-defined modal split, the dataset directly facilitates the identification of trips with genuine battery swap requirements, eliminating the need to hypothetically distribute modal preferences within an O-D matrix.

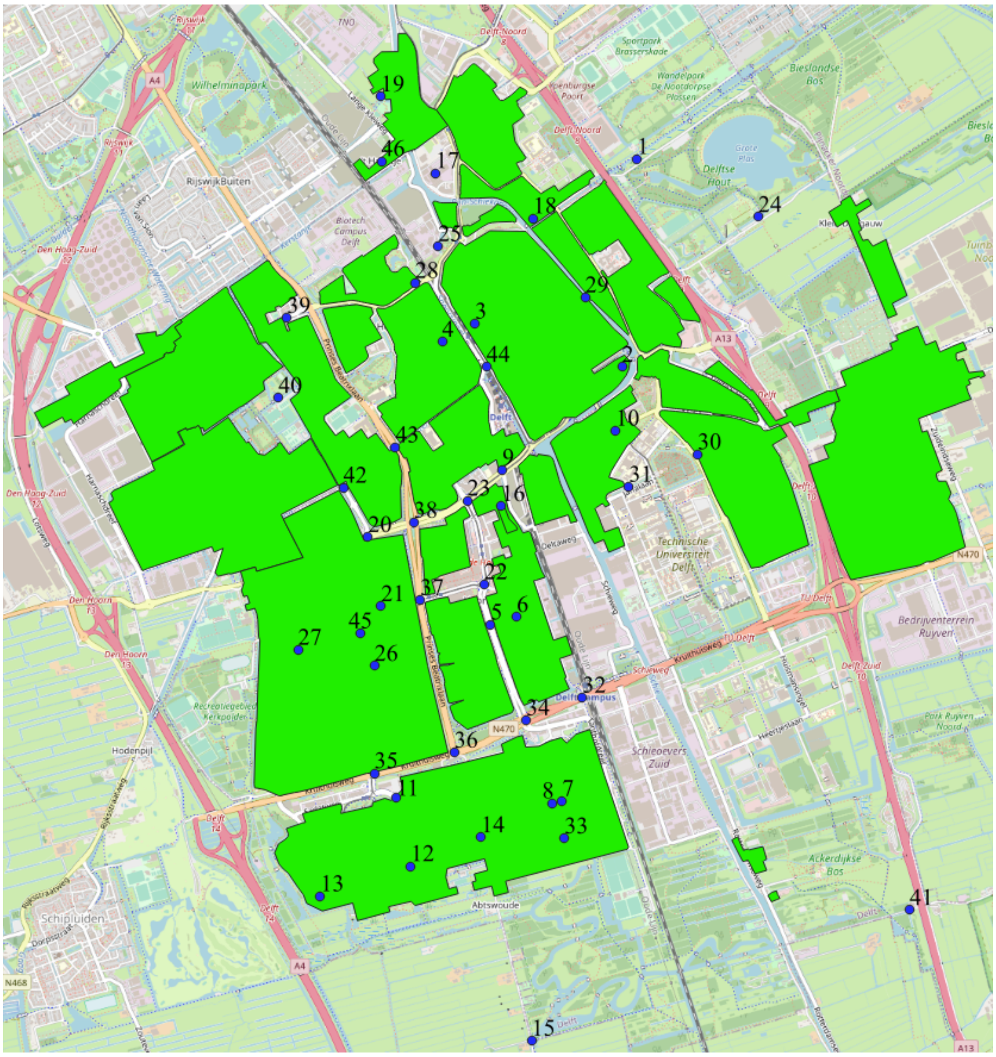


Figure 4.1.2 Residential areas in Delft (identified by QGIS with data source from Openstreetmap)

However, there are also certain limitations associated with this dataset. For instance, 1) the dataset contains a relatively modest number of trips. As previously demonstrated, the actual total number of trips within this dataset stands at 68,640, which, for an urban traffic network, does not constitute a substantial sample. Among these trips, many do not involve modes requiring battery swaps at public BSSs. Consequently, the total battery swapping demands identified from this dataset could be comparatively small. Given that the established model exclusively accounts for the travel time of vehicles with battery swapping requirements, it disregards the travel time of other vehicles, which merely traverse the shortest path between their origins and destinations. Consequently, the aggregate travel time computed by the model may also be minimal, potentially leading to a situation where construction costs dominate over the economic impact of travel time. This inclination could render the model less responsive to certain variations. 2) The dominance of residential land use within the city poses a challenge. Notably, Figure 4.1.2 delineates the residential land use in Delft (represented by green areas), as identified using OpenStreetMap within QGIS. Evidently, the majority of the citys expanse consists of residential areas, with a significant proportion of network nodes situated within this context. This composition may complicate efforts to avoid situating stations within residential zones. Furthermore, certain nodes beyond the residential scope lack favorable conditions for station construction. Take Node 44, for instance, located on a road flanked by two green blocks, yet encircled by a railway station, a river, retail establishments, and residential structures. Erecting a Battery Swapping Station at such a node would be impractical. These circumstances amplify the likelihood of station construction within residential areas. 3) As illustrated earlier, certain nodes lack the prerequisites for BSS construction. Importantly, the nodes within this network do not coincide with the centroids of city zones; they are select points within Delfts traffic network and do not accurately represent distinct city areas. Hence, disregarding the genuine construction context within this network could potentially engender unrealistic solutions, potentially compromising the authenticity of the proposed solution.

Regarding the solutions authenticity concerning the actual construction feasibility at each node, it is possible to scrutinize the positions of the 46 nodes on a satellite map prior to initiating the optimization process. For nodes deemed unsuitable for Battery Swapping Station (BSS) placement due to impracticality, constraints can be incorporated into the model to prohibit construction in such locations.

For this specific case study, not all the information within this dataset will be utilized. As outlined in Section 3, the essential datasets for the formulated model encompass the node set, link set, link weight set, demand matrix, the shortest path set, and vehicles' origin-destination (OD) set. While most of these sets are readily available within the Delft dataset, certain aspects like the set of shortest path lengths necessitate data processing to be derived from the raw data. Additionally, given that the dataset includes numerous trips not involving car, truck, or coach modes, these trips inherently lack battery swapping demands. Consequently, this subset of data needs to be filtered out from the dataset before incorporation into the model. This pivotal process will be introduced in the ensuing subsection.

4.2 Data processing

This subsection will illustrate how the raw dataset is processed to obtain the data that is necessary for this case study.

4.2.1 Obtaining the shortest path length between each O-D pair

The first data to be processed is the network data. The shortest path lengths between all pairs of nodes are critical for conducting later calculations in the model. Since the raw dataset only contains the nodes, links, and link travel times, the shortest path length between each pair of nodes is not available in the raw dataset. However, it is easy to derive the shortest path lengths with the data provided by the raw dataset using the functions inserted in Python. The network is first constructed using the "*networkx*" package in Python by inputting the nodes, links, and link travel times into the function. Then, with the "*shortest_path_len()*" function, the shortest path lengths between all pairs of nodes will be calculated using the Dijkstra algorithm. For the convenience of later use, a dictionary is created to store the shortest path length data in the form "*(x, y): z*", in which, x and y are the ID of the origin node and the destination node. z is the shortest path length between these two nodes.

So far, the first step of the data processing has been completed, and the shortest path lengths are available as model input.

4.2.2 Filtering out trips without battery swapping demands

It has been mentioned in Section 4.1 that many trip modes will never have battery swapping demands, thus they shall be filtered out from the raw dataset.

The raw dataset collects trips with seven different traffic modes, including 1: walking trips, 2: bicycle trips, 7: car (driver) trips, 8: car (passenger) trips, 9: train, light rail trips, 12: taxi trips, 15: disable trips. Where the numbers are the ID of each traffic mode. Among these seven modes, only mode 7 (car driver trips) and mode 12 (taxi trips) can have battery swapping demands. All other trips have no possibility to swap the battery for their transportation tools. Therefore, for the raw dataset, only trips with mode 7 and mode 12 will be kept for future processing. All other trips will be removed from the dataset in this case study. In total, there are 1154 trips among 3432 trips (all proxy numbers) using mode 7 and mode 12 for traveling. This is the first step for determining the battery swapping demands.

The second step is to compare each vehicle's initial SOC and the shortest path length between its origin and destination to confirm if it actually has battery swapping demands. This judging method has been explained in Section 3 with Formula (1), (2), (3), and (4). The initial SOC (in percentage) of each vehicle will be randomly drawn from the probability density function (Equation (3)). And the specific rest mileage that can be traveled by a vehicle before its battery runs out will be calculated using Equation (4). Then, by comparing the calculation results of Equation (4) and the shortest path length between the vehicle's origin and destination, the battery swapping demand of this vehicle can be confirmed. Only vehicles that are confirmed to have battery swapping demands will be input into the model for doing experiments. Vehicles without demands will be removed from the vehicle set.

It is crucial to further specify that generating the initial SOC for each vehicle using a probability density function can introduce substantial uncertainty, particularly when the number of samplings is limited. This uncertainty, in turn, can impact the reliability of the final optimization outcomes and related analyses. To address this concern, a total of eight sets of initial SOCs have been drawn, and all sets will undergo testing within this case study to assess the extent to which the initial SOC values influence the location results. The decision to opt for eight initial SOC sets stems from the goal of extracting sufficient information from these sets, enabling confirmation of the degree of uncertainty through experimentation. Importantly, utilizing eight sets will not excessively burden the models computational load.

4.2.3 Confirm construction conditions at each node

As illustrated in Subsection 4.1, to guarantee the authenticity of the solution, it is necessary to check if is realistic to construct a BSS at each node on the satellite map. After conducting the confirmation, nodes that are possible to have a station constructed there are shown in Table 4.2.1:

Table 4.2.1 Node locations (can build BSS)

Area	*Node*
Residential	[2, 6, 11, 12, 13, 14, 16, 18, 21, 22, 26, 27, 28, 30, 33, 39, 45, 46]
Non-residential	[1, 5, 9, 15, 17, 19, 20, 23, 24, 25, 32, 34, 35, 36, 37, 38, 40, 41, 43]

Among the entirety of 46 nodes, Node 3, 4, 7, 8, 10, 29, 31, 32, 42, and 44 lack the necessary construction conditions for BSSs. Specifically, Node 3, 4, and 44 are situated in proximity to the city centers periphery, enveloped by a combination of a railway station, a river, a multitude of retail outlets, office edifices, and residential abodes—rendering these locales unsuitable for station establishment. Node 7 and 8 find themselves ensconced within densely populated residential enclaves, with the presence of a primary school in close proximity. Node 10 and 31 bear close proximity to a cemetery. Meanwhile, Node 29 and 42 abut a river and a diminutive bridge, thereby elevating the safety risks for passing vehicles.

4.3 Scenario settings

As highlighted at the inception of Section 4, this case study intends to explore impacts of several possible situations: the stochastic nature of Electric Vehicle (EV) initial SOC, the maximal travel range of EVs, the station size limits, and optimization preferences—encompassing considerations for enhanced travel time, reduced station count in residential areas and minimized economic outlays. Experiments conducted under diverse EV maximal travel ranges can unveil the influence of battery technologys evolution. In an er a where EV manufacturers are progressively introducing vehicles with extended travel ranges, discerning the consequences of this technological advancement on future infrastructure planning becomes significantly consequential. Within this case study, the station size limits predominantly reflect the context of urban livability, thus imposing limits exclusively upon stations sited in residential areas. Such an exploration can shed light on how concerns for urban quality of life may decisively sway the entirety of the planning process. Furthermore, it serves to quantify the "price" that must be borne—comprising both additional economic expenditure and potential traffic network travel time increments—for the realization of these considerations. Varied optimization preferences are capable of emulating the multifaceted considerations of decision-makers across distinct scenarios. These preferences denote the varying significance attributed to three pivotal stakeholders: system investors, urban residents, and system users, as perceived by the decision-maker. For instance, when the municipal administration vested with determining the final layout of BSSs seeks to economize on construction expenses, a weighty emphasis will be placed upon the total economic outlay within the objective function. Conversely, if the aim is to curtail travel time within the traffic network, thereby enhancing the citys operational efficiency, an amplified weight will be assigned to the travel time variable within the objective function. Such preference-based dynamics typify the intricacies of real-world decision-making processes, thus warranting a comprehensive exploration of the potential planning scenarios contingent upon varying optimization preferences. This endeavor holds the potential to significantly inspire and guide decision-makers.

4.3.1 Basic parameter settings

In this case study, in total, nine scenarios will be set up to explore the impacts of a wider EV traveling range, potential station size limit in the residential area, and preferences including for a better travel time, for fewer stations in the residential area, and for lower station construction cost, on the optimization. Specific scenario settings will be introduced in this subsection later.

Before setting up all nine scenarios, it is necessary to determine all other parameter inputs of the model first so that the experiment can be completed. These parameters will be fixed for all scenarios.

Table 4.3.1 summarizes all needed parameter inputs of this model in the case study:

Table 4.3.1 Basic parameter settings of the case study

Parameter	***Value***
f_c	1,000,000 euros
f_r	1,500,000 euros
f_s	500,000 euros
w	3 min
VoT	0.3 euro/min
T	10 years

These parameters have been introduced in Section 3. f_c is the construction cost of a station outside the residential area with the most basic station size (can serve less than 100 vehicles a day), cited from Li et al. (2022). f_r is the construction cost of a station in the residential area with the most basic station size. The extra cost compared to f_c consists of the cost of building sound barriers around the station (cost around 300,000 euros, according to the data from Federal Highway Administration, U.S. Department of Transport) and extra land for increasing the distance between battery batches stored in the station (cost around 200,000 euros according to Li et al. (2020)). f_s is the price that needs to be paid by a station for upgrading once. This is estimated by the price of batteries and land price. w is the waiting time (including the service time and entering, leaving time). VoT is the Value of Time, cited from Goldszmidt et al. (2020). T is the lifespan of the BSS, which is cited from Krim et al. (2022). This study conducted an investigation on the lifespan of a BCS considering its hardware and software. Since facilities in a BSS and a BCS can be quite similar to each other, the investigation result in this study is used in this case study.

4.3.2 Impact of EV maximum traveling range (battery swapping demands)

Table 4.3.2 exhibits the settings of Scenario 1, 2, and 3, which are to explore the impacts of different EV maximum traveling ranges on the planning results.

Table 4.3.2 Settings of Scenario 1, 2, and 3

Scenario	*Maximum traveling range of EVs*	*Station size limit (residential areas)*	*Stakeholder weights*
1	100 km	NO LIMIT	[1, 1, 1]
2	200 km	NO LIMIT	[1, 1, 1]
3	300 km	NO LIMIT	[1, 1, 1]

Across these three distinct scenarios, the EV maximal traveling range will be systematically varied, spanning from 100 km to 200 km and further extending to 300 km. While contemporary EVs are capable of exceeding 300 km, the upper threshold for these experiments is set at 300 km, as the traffic network underpinning this case study is characterized by its modest scale. Elevating the vehicles travel range excessively might result in a diminished, or even negligible, identification of battery swapping demand within the network. The parameter of station size limitation, in turn, will exclusively apply to stations situated within residential zones. In the context of these three scenarios, station size constraints will be omitted, given that the primary focus lies in dissecting the repercussions of varying EV maximal traveling ranges. Meanwhile, the allocation of weights to stakeholders conveys their equitable significance within the model. In this formulation, parity is upheld, signifying that all three stakeholders are endowed with equal importance.

As the Electric Vehicle (EV) maximal traveling range increases, corresponding to a reduction in battery swapping demands, these scenarios are anticipated to yield progressively fewer stations within the network, or alternatively, to result in diminishing station sizes.

It is necessary to specify that Scenario 1 can be the base case for all scenarios tested in this case study. Every scenario can be compared to Scenario 1 to analyze the specific impact of a certain measure.

4.3.3 Impact of station size limit

Table 4.3.3 exhibits the settings of Scenario 4, 5, and 6, which are to explore the impacts of different station size limits on the planning results.

Table 4.3.3 Settings of Scenario 4, 5, and 6

Scenario	*Maximum traveling range of EVs*	*Station size limit (residential areas)*	*Stakeholder weights*
4	100 km	≤ 100 veh	[1, 1, 1]
5	100 km	≤ 200 veh	[1, 1, 1]
6	100 km	≤ 300 veh	[1, 1, 1]

Since these three scenarios are to test the impacts of different station size limits, the maximum traveling range of EVs is fixed for three scenarios here. The reason for setting the maximum traveling range of EVs to 100 km is that when the maximum traveling range of EVs reaches 200 km, the demand becomes really low in this city. To guarantee that there will be comparable results obtained from different scenarios, it is better to have more demands in the network. And the importance is still the same for all three stakeholders.

It is expected that for these three scenarios, they will produce more stations or bigger stations outside the residential area compared to Scenario 1, thus the number of stations or the size of stations in the residential area will decrease. Besides, the average travel time per vehicle can be longer than that in Scenario 1 because the station size limit will affect the original optimal solution produced by Scenario 1. To reach a better urban liability level, some vehicles must have a longer detour than the original case to get their demands met outside the residential area.

4.3.4 Impact of optimization preference

Table 4.3.4 exhibits the settings of Scenario 7, 8, and 9, which are to explore the impacts of different optimization preferences on the planning results.

Table 4.3.4 Settings of Scenario 7, 8, and 9

Scenario	***Maximum traveling range of EVs***	***Station size limit (residential areas)***	***Stakeholder weights***
7	100 km	NO LIMIT	[1, 1, 3]
8	100 km	NO LIMIT	[1, 3, 1]
9	100 km	NO LIMIT	[3, 3, 1]

Since these four scenarios are to test the impacts of different optimization preferences, the maximum traveling range of EVs is set to 100 km for all four scenarios, for the same reason illustrated in Subsection 4.3.3. And there is no station size limit for stations constructed in the residential area.

Scenario 7 assigns a weight of 3 to system users, which means that the decision-maker considers network travel time more important than the construction costs of stations. The reason for setting this weight to 3 is that there should be more emphasis on the importance of network travel time so that there will be a different planning result obtained from this scenario, meanwhile, this weight will not make travel time dominate the optimization. The weights on the other two terms of the objective function are still 1 so this scenario only simulates the preference for the better travel time. This scenario is expected to output more stations in the network, or the service demands will be distributed widely in the network so that the minimum travel time can be reached.

Scenario 8 assigns a weight of 3 to urban residents' interests, which means that the decision-maker considers the construction costs of stations in the residential area more important than the other two terms. This scenario is expected to produce a smaller number of stations or smaller station sizes in the residential area. The overall result of this scenario can be similar to those in Scenario 4, 5, and 6 because these scenarios all discourage station construction in the residential area.

Scenario 9 assigns a weight of 3 both to the construction cost of stations both inside and outside residential areas. Therefore, this scenario is to discover what the planning result will be if the decision-maker considers the economic expenditure of constructing stations more important than the traffic network performance. Under this circumstance, this scenario is expected to output fewer stations in the network, or, the service demands will be gathered to a single or several stations and as a result, there will be big stations in the network so that the economic expenditure will be saved to the greatest extent. And the network travel time will be longer compared to Scenario 1.

4.4 Key performance indicators (KPIs)

Multiple groups of scenarios have been built in Subsection 4.3. It is expected that these scenarios will lead to different optimal solutions for BSS's locating problem in the Delft network. Analyzing these results can bring much information about the properties and performance of the established model, but it is not enough to analyze the results only based on the locating results. There should be indicators showing different aspects that can be affected by the location decision. This subsection will introduce several Key Performance Indicators (KPIs) that will be used for evaluating the optimal solutions in this case study and build a solid foundation for the analyses in later subsections.

4.4.1 Service density per station - S_{dense}

The first indicator is the average service density of stations S_{dense}, which can be calculated by:

$$S_{dense} = \frac{D}{N_{sta}} \tag{22}$$

Where, D is the total battery swapping demands identified in the network. N_{sta} is the total number of stations constructed. Therefore, service density per station is the average number of vehicles that will be served by each station in the network.

Service density per station can partly reflect the efficiency of the solution. For example, if there are two different solutions for the same number of service demands, Solution 1 requires fewer stations than Solution 2, one can probably say that Solution 1 is more efficient than Solution 2 because it deals with the same number of service demands with less number of stations. For system investors who only care about their economic investments in this system, Solution 1 is absolutely a better choice than Solution 2. However, this thesis does not only consider system investors' interests, there are also considerations for urban residents and system users. That is the reason why the total number of stations in a solution can only partly reflect the efficiency of a solution. Still taking Solution 1 and Solution 2 described before as the example, if Solution 1 satisfies all the service demands in the network with fewer stations than Solution 2, but produces a much greater total travel time in the network than Solution 2, then one cannot conclude that Solution 1 must be more efficient than Solution 2. From system users' perspective, who do not care about the economic investments of the system, Solution 2 is absolutely a better choice for them than Solution 1 because they spend less time on traveling with Solution 2's location decision. This example also shows that it is quite necessary to design multiple standards for solution evaluation. Otherwise, the analyses would be biased a lot and the performance and properties of the established model cannot be properly concluded. In the first three scenarios, this indicator can reflect the cost performance of the investment in constructing BSSs to a great extent.

4.4.2 The number of stations in the residential area - N_r

Then the second indicator is the number of stations N_r constructed in the residential area. It has been illustrated in Section 2 and Section 3 that a station constructed in the residential area can have non-negligible negative impacts on residents' quality of life. Therefore, the number of stations constructed in the residential area is an important indicator to evaluate how much a solution will affect urban livability. Although noise mitigation and safety enhancement measures are taken to benefit urban residents, they only alleviate the negative impacts on people's lives, do not entirely eliminate these impacts, and do not enhance the livability level compared to a condition where no station is constructed in the residential area. In Scenario 4, 5, 6, and 8, this indicator can clearly reflect the impacts of different strategies on the station distribution in the traffic network.

4.4.3 Service demands met inside and outside the residential area – D_r and D_c

The third and fourth indicators are the service demands satisfied inside and outside the residential area in a day. These two indicators are to reflect the service demands distribution (where the demands are met, not where the demands come from) in the traffic network. They can be related to the overall station sizes in two areas of the city, or the number of stations in the two areas. Besides, by combining these two indicators with travel time information, it can be inferred whether locating stations in a certain area will reduce or increase the network travel time.

4.4.4 Total network travel time - NTT

The fifth indicator is the total network travel time *NTT* in a day, which can be directly output by the model. This is a critical indicator for evaluating the performance of a traffic network. In this model, the network travel time only considers the time spent by vehicles with battery swapping demands because only these vehicles have to detour to enjoy the service, thus only these vehicles' travel time will be affected by the spatial distribution of BSSs in the network while all other travelers will travel along the shortest paths between their origins and destinations. This indicator is an overall evaluation standard for the entire traffic network, but it is not suitable to compare *NTT* of two solutions under any conditions. It is meaningful to compare the network travel times of two solutions only when the numbers of vehicles considered by the two solutions are the same. It is unfair to compare *NTT* if two solutions deal with different numbers of demands because more demands tend to produce greater total travel time in the network. Therefore, it is necessary to introduce another indicator to express network efficiency, which is the fifth indicator in this case study.

4.4.5 Average travel time per vehicle - ATT

The sixth one is the average travel time per vehicle *ATT*. Like the total network travel time, *ATT* also only considers the travel time of vehicles that have battery swapping demands. The calculation function of *ATT* can be written as:

$$ATT = \frac{NTT}{N_{veh}} \tag{23}$$

Where, N_{veh} is the total number of vehicles considered in the model. As has been mentioned in 4.4.4, *NTT* cannot reflect the transport efficiency of the network because it is unfair to compare the *NTT* of two solutions with different vehicle numbers. *ATT* successfully resolves this problem. The average travel time per vehicle is closely related to the size of the detour experienced by the driver. Generally speaking, it reflects how convenient it is for drivers to have battery swapping services under a certain spatial distribution of BSSs. However, there is still another problem. The average value can be easily affected by extreme values. To be specific, in this case study, the intra-node travel time is set to be 0, thus some vehicles can have no detours at all even if they have battery swapping demands (for example, a station is located at a vehicle's origin or destination node). Then the average travel time can be hugely affected by this part of vehicles (leading to the underestimation of average travel time per vehicle) while some other vehicles are actually experiencing serious detours at the same time. This indicates the necessity for introducing the last indicator related to travel time.

4.4.6 Standard deviation of travel time - STD-TT

The standard deviation of travel time can perfectly reflect the degree of the influence of extreme values on the average value. A lower *STD-TT* indicates a more reliable average travel time. Therefore, with *STD-TT*, one's evaluation of the average travel time can be more robust. The calculation function of STD-TT is written as the following:

$$STD\_TT = \sqrt{(t_i - ATT)^2} \tag{24}$$

Where, t_i is the travel time of vehicle *i*.

For the solution with a smaller *STD-TT* than others, it is believed that this solution has a more reliable *ATT* than other solutions.

4.4.7 Total construction costs of stations inside and outside the residential area – C_r and C_c

In previous subsections, indicators that focus on the spatial distribution of stations, demand distribution, and network travel time all have been introduced. The rest indicators will focus on the economic expenditure of the solution. C_r and C_c together reflect system investors' money spent on constructing stations.

4.4.8 Station construction cost per vehicle – AC

The economic cost per vehicle can reflect how much money shall be spent to meet one vehicle's battery swapping demand in the network during stations' lifespan, which can be calculated by:

$$AC = \frac{C_r + C_c}{D} \tag{26}$$

This indicator tells the socioeconomic efficiency of a solution. For the optimization situation represented by Scenario 9, this indicator can directly show the economic benefit that can be brought to society by this kind of preference.

To sum up, these ten indicators together evaluate a solution's quality from the perspectives of 1) spatial distribution of stations, 2) distribution of service demands, 3) traffic network performance, 4) economic expenditure of system investors, which include the interests of all three stakeholders considered in this model. The results analyses in the next subsection will be totally based on these indicators so that for each solution, there can be a comprehensive comment.

4.5 Results and analyses

Within this subsection, we shall present the experimental outcomes of the uncertainty assessment pertaining to the randomness of EV's initial SOC, alongside results derived from nine distinct scenarios. Comprehensive analyses will be conducted to uncover the underlying rationales driving the divergences observed among these scenarios. In order to attain a holistic comprehension of the models characteristics and discern the underlying factors contributing to specific scenario outcomes, supplementary explanatory experiments beyond the pre-defined nine scenarios will be executed and scrutinized within this subsection. These supplemental experiments serve to provide auxiliary insights. The discussions encompassing each scenario will be broadly delineated into two key segments: descriptions of the experimental results and comprehensive analyses of the obtained outcomes.

Each scenario is run on an Intel ® Core™ i7-10875H CPU@2.30 GHz computer with 16GB RAM. The optimization model is programmed using Python and solved by Gurobi Optimizer Version 10.0.0. The solving time of the developed model is not long. All nine scenarios can be solved within 40 seconds.

4.5.1 Location uncertainty test

Before doing experiments in nine scenarios, the first thing to do is to test how much uncertainty the randomly generated vehicles' initial SOCs will bring to the location results of stations in Delft. Table 4.5.1 shows the optimal station locations in Delft corresponding to eight random initial SOC sets while considering the construction limit at each node (so nodes that are unsuitable for constructing a BSS are excluded).

Table 4.5.1 Station locations under different vehicle initial SOCs

Sequential number of initial SOC set	***Optimal station locations***
1	No feasible solution
2	[5, 27, 28, 30, 35, 43]
3	[5, 9, 27, 28, 30, 35, 43]

4	[2, 5, 14, 27, 28, 43]
5	No feasible solution
6	No feasible solution
7	No feasible solution
8	No feasible solution

Out of the eight sets considered, five yield results indicating the absence of a feasible solution. This outcome may be attributed to the service constraint inherent in the model, stipulating that each vehicle with a battery swapping demand must have access to a station within its operational travel range. For vehicles with initial SOC values on the lower spectrum, the inability to access a battery swapping station before their energy depletes, particularly when constrained by the exclusion of certain nodes from Battery Swapping Station (BSS) construction, could underlie this situation. To substantiate this hypothesis, a supplementary and straightforward experiment was conducted under the purview of the first set of randomly generated initial SOC values, which initially yielded an infeasible optimal solution. In this auxiliary experiment, the residual travel distance for each vehicle was constrained to 100 km. The outcome revealed an attainable optimal solution under these conditions. This experimental observation serves as evidence, affirming that the absence of feasible solutions results from the imposition of construction limits, which impede the fulfillment of battery swapping demands for specific vehicles.

Therefore, subsequent auxiliary experiments are to find out which excluded nodes can be critical for meeting all battery swapping demands in the city. In this case, the construction limit is ignored temporarily in the next group of experiments. And Table 4.5.2 shows the optimal location results under this circumstance:

Table 4.5.2 Station locations under different vehicle initial SOCs (without construction limit)

Sequential number of initial SOC set	***Station locations***
1	[3, 5, 27, 31, 35]
2	[3, 5, 27, 30, 35]
3	[3, 5, 27, 30, 36]
4	[3, 5, 10, 14, 27]
5	[3, 5, 27, 30, 35]
6	[3, 5, 13, 27, 30]
7	[3, 5, 27, 31, 35]

8	[2, 3, 5, 12, 27]

From Table 4.5.2, it can be noticed that there are three locations that appear quite frequently under every initial SOC set – Node 3, 5, and 27. Among these three locations, Node 5 and 27 are considered suitable for constructing BSS, but Node 3 is surrounded by a railway station, a river, residential houses, and retail shops, thus unrealistic to construct a station there.

Since Node 3 appears as one of the candidate locations under every initial SOC set, the next auxiliary experiment relaxes the constraint that no station can be constructed at Node 3 and keep the constraints holding for other nodes. Table 4.5.3 exhibits station locations under this condition:

Table 4.5.3 Station locations under different vehicle initial SOCs (no construction limit for Node 3)

Sequential number of initial SOC set	***Station locations***
1	[3, 30, 34, 35, 45]
2	[3, 5, 27, 30, 35]
3	[3, 5, 27, 30, 35]
4	[2, 3, 5, 14, 27]
5	[3, 5, 27, 30, 35]
6	[3, 5, 13, 27, 30]
7	[3, 5, 27, 31, 35]
8	[2, 3, 5, 12, 27]

Upon the relaxation of the construction constraint at Node 3, it becomes evident that a feasible optimal solution endures across all sets of randomly generated initial SOC values. This revelation underscores the pivotal role Node 3 assumes within the intricate fabric of the traffic network. This centrality is chiefly manifested through two distinct dimensions. Primarily, a multitude of vehicles with battery swapping requirements either originate from nodes proximate to Node 3 or directly emanate from this pivotal node itself. Secondly, Node 3 is situated along the shortest trajectories of numerous Origin-Destination (O-D) pairs, rendering it a node inherently conducive to achieving minimal travel durations. For a substantial subset of vehicles necessitating battery swaps, opting for Node 3 as the station location entails a comparably reduced detour when contrasted with alternative nodes. This dual constellation of factors firmly positions Node 3 as an "inescapable" locus for potential Battery Swapping Station (BSS) establishment within Delft City. Nevertheless, the real-world application of this choice is not devoid of complexities, as Node 3s contextual surroundings pose formidable challenges to the design and realization of a BSS. This inherent clash between strategic planning and practical construction encapsulates a significant dilemma.

4.5.2 Impact of EV maximum traveling range

This subsection will start the analyses on the nine scenarios. It is imperative to elucidate that meaningful comparisons across these scenarios necessitate their evaluation against a uniform backdrop of randomly generated initial SOC values. Moreover, the inherent construction constraint must be rigorously upheld throughout the analyses. To this end, the second, third, and fourth sets of randomly generated initial SOC values will be reserved for subsequent experiments, given their capability to yield feasible optimal solutions within the context of a comprehensive construction constraint across the city. Primarily, the analyses will predominantly draw from the results garnered under the second initial SOC set. This choice is rooted in the overarching similarity of implications observed across these three distinct sets. Notably, the third and fourth sets are incorporated as supplementary experimental variants, introducing an element of controlled randomness into the outcomes. Consolidated within Table 4.5.4 are the comprehensive numerical outcomes spanning all nine scenarios, each evaluated under the purview of the second set of randomly generated initial SOC values.

Table 4.5.4 Overall numerical results of nine scenarios

Scenario	***Station locations***	***C_c (euro)***	***C_r (euro)***	***S_{dense}***	***NTT (min)***	***ATT (min)***	***STD-TT (min)***
1	[5, 27, 28, 30, 35, 43]	5,500,000	9,000,000	317	60,190	31.679	3.944
2	[9, 27, 43]	3,500,000	4,500,000	220	23,430	35.500	1.606
3	[27, 43]	1,500,000	1,500,000	180	9,100	35.000	0.032
4	[5, 27, 28, 30, 35, 43]	10,000,000	4,500,000	317	61,890	32.574	4.195
5	[5, 27, 28, 30, 35, 43]	9,500,000	5,000,000	317	61,570	32.405	4.032
6	[5, 27, 28, 30, 35, 43]	9,000,000	5,500,000	317	61,340	32.284	3.956
7	[5, 14, 28, 30, 43, 45]	3,000,000	12,000,000	317	59,940	31.547	4.039
8	[5, 27, 28, 30, 35, 43]	10,000,000	4,500,000	317	61,890	32.574	4.195
9	[5, 28, 30, 35, 45]	5,000,000	8,500,000	380	62,510	32.900	6.094

Continued table 4.5.4

Scenario	N_{sta}	N_r	D_c	D_r	***Demand distribution***	***Total construction cost (euro)***	***AC (euro)***
1	6	3	800	1,100	[400, 980, 60, 60, 100, 300]	14,500,000	7631.579
2	3	1	460	200	[60, 200, 400]	5,500,000	8333.333
3	2	1	130	180	[80, 180]	3,000,000	11538.460
4	6	3	1,660	240	[700, 100, 80, 60, 160, 800]	14,500,000	7631.579
5	6	3	1,600	300	[700, 180, 60, 60, 100, 800]	14,500,000	7631.579
6	6	3	1,500	400	[700, 280, 60, 60, 100, 700]	14,500,000	7631.579
7	6	4	400	1,500	[100, 380, 60, 60, 300, 1000]	15,000,000	7894.737
8	6	3	1,660	240	[700, 100, 80, 60, 160, 800]	14,500,000	7631.579
9	5	3	800	1,100	[700, 300, 100, 100, 700]	13,500,000	7105.263

In Scenario 1, 2, and 3, the most obvious change is that the number of BSSs in the city decreases. There are 6, 3, and 2 BSSs constructed under Scenario 1, 2, and 3, respectively. Correspondingly, the average service density S_{dense} also decreases, along with the increase of AC. Optimal station locations in these three scenarios are visualized in Figure 4.5.1, Figure 4.5.2, and Figure 4.5.3.

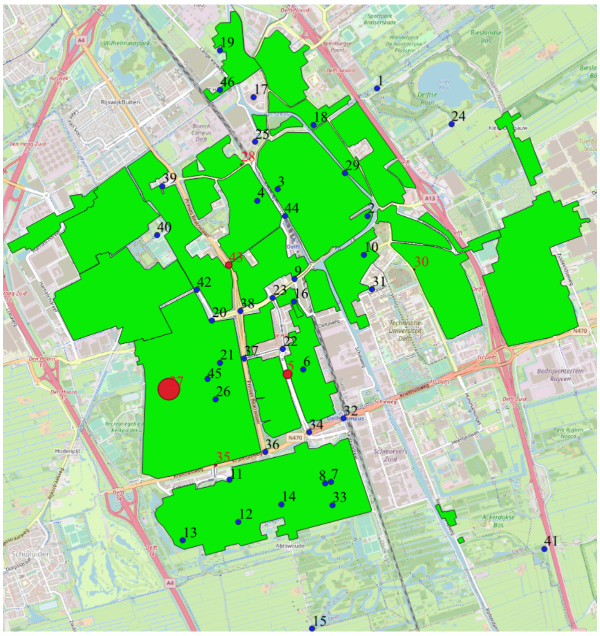


Figure 4.5.1 Scenario 1

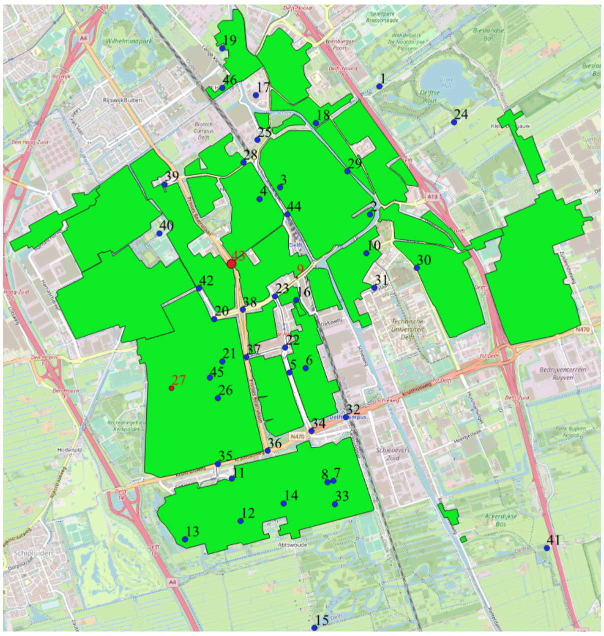


Figure 4.5.2 Scenario 2

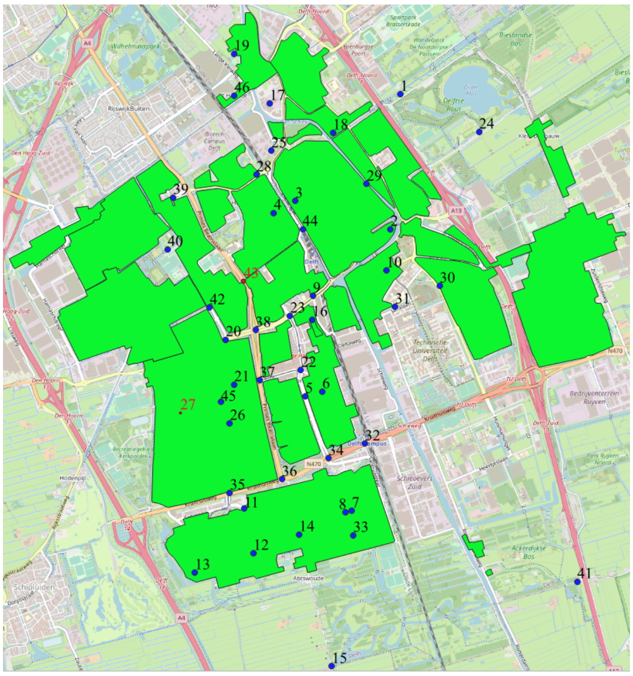


Figure 4.5.3 Scenario 3

In above figures, red dots represent station locations, the sizes of these red dots represent the size of BSSs, which are the number of vehicles to be served by these stations in a day. It is intuitionistic in these three figures that the number and the size of BSSs keep decreasing from Scenario 1 to 3.

To make AC and S_{dense} of the three scenarios also more intuitionistic, two scatter plots are made and exhibited in Figure 4.5.4 and Figure 4.5.5.

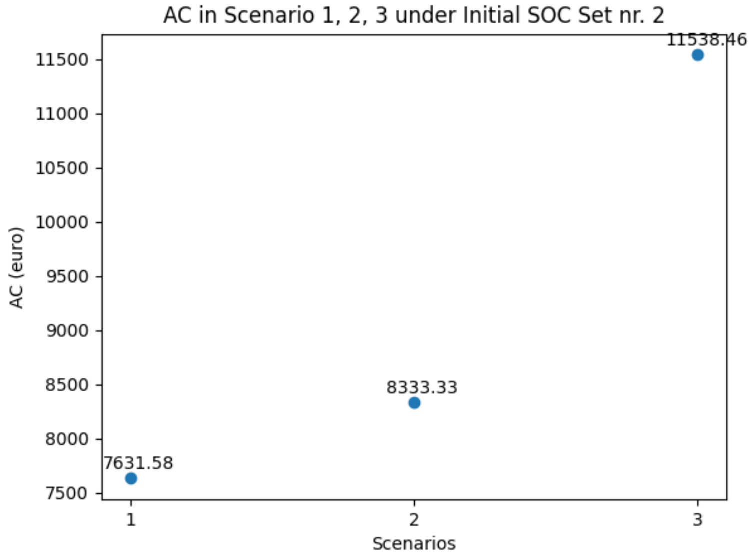


Figure 4.5.4 AC in Scenario 1, 2, and 3

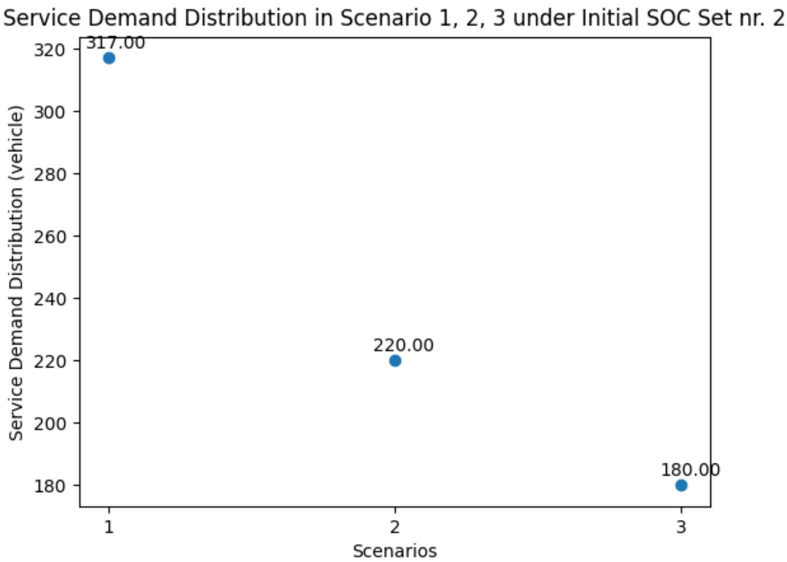


Figure 4.5.5 S_{dense} in Scenario 1, 2, and 3

From the above two figures, it can be observed that AC increases rapidly and S_{dense} decreases with the decrease of the battery swapping demands. The fulfillment of battery swapping demands within the traffic network holds significance as a societal benefit. The more vehicles that a station serves in a day, the more benefits this station will bring to society. This phenomenon fundamentally mirrors the investment efficiency in station construction endeavors. Evidently, Scenario 3, among the trio of scenarios, exhibits suboptimal investment efficiency because the basic construction cost of stations is the same as that in Scenario 1 and 2, but the average number of vehicles that will be served at each station in the network is much less than the previous two scenarios. The results of these three scenarios can provide inspiration for the planners that future infrastructure planning can be made on a larger scale, for example, on a regional level, including several cities and highway networks among these cities. From these three scenarios, it can be noticed that the daily battery swapping demands that can be identified in a city's traffic network will hugely decrease as EV's maximum traveling range becomes higher and higher. In this case study, the highest EV maximum traveling range is only 300 km. Nowadays, many EVs can have a much wider traveling range than 300 km with a fully charged battery, which means that the potential battery swapping demands in the future in the real world can even be lower than the number identified in this case study. If keep making location planning for infrastructures in a single city, the investment will be quite inefficient. The economies of scale cannot be achieved. However, considering a larger scale can include more demands in the planning. This can lead to more flexible planning. There can be some buffers for the decision-maker to deal with trade-offs. Besides, a larger traffic network can include interactions among different cities. This allows the model to consider the battery swapping behavior in the highway network, which helps make the planning more practical.

The experiment results obtained under the third and fourth random initial SOC sets showed another possible situation that Scenario 2 and Scenario 3 can have the same number of BSSs though Scenario 3 has fewer demands than Scenario 2. This is still because of the service constraint of the model. Sometimes, although the total number of demands is small, some vehicles have quite low initial SOCs, and thus cannot travel too far away from their origins. In this case, there must be a station near them. Therefore, it is also possible that the total number of BSSs in the city did not decrease from Scenario 2 to Scenario 3.

To sum up, Scenario 1, 2, and 3 explore the impact of EV's maximum traveling range on the location planning of BSSs. It is found that the increasing EV maximum traveling range will make the daily battery swapping demands that can be identified in a city's traffic network rapidly decrease. As a result, the cost performance will also decrease with smaller and smaller demands, which means that the investment in constructing BSSs in the city will become less efficient. Based on these experiment results, the planners can get inspiration that the location planning of BSSs should be made on a larger traffic network, for example, on a regional level, which includes several cities and highway traffic networks among them. This can help to reach the economies of scale in the investment stage and capture the battery swapping behavior in the highway networks. In these three scenarios, the traffic network performance is not analyzed because the three scenarios correspond to different battery swapping demands in the city. Since the network travel time (both *NTT* and *ATT*) will be influenced by the demand distribution characteristics in the city, it is not that meaningful to compare the traffic network performance among these three scenarios. For the same reason, it is hard to predict how the number of stations in the residential area will change as the traveling range of the EV increases. Therefore, it is difficult to directly draw an overall conclusion about the impact of EV technology development on urban livability. The specific condition is highly dependent on the demand distribution characteristics in the city.

4.5.3 Impact of the station size limit

Scenario 4, 5, and 6 are to explore the impact of setting a station size limit on the optimal location decision-making. Three levels of limit are tested in these three scenarios. Scenario 4 has the strictest regulation. From Scenario 4 to Scenario 6, this limit is gradually relaxed.

From numerical results, it can be observed that compared to Scenario 1, the station locations in

Scenario 4, 5, and 6 do not change. Only the size of each station changes due to this limit. The station location results of these three scenarios are visualized in Figure 4.5.6, Figure 4.5.7, and Figure 4.5.8.

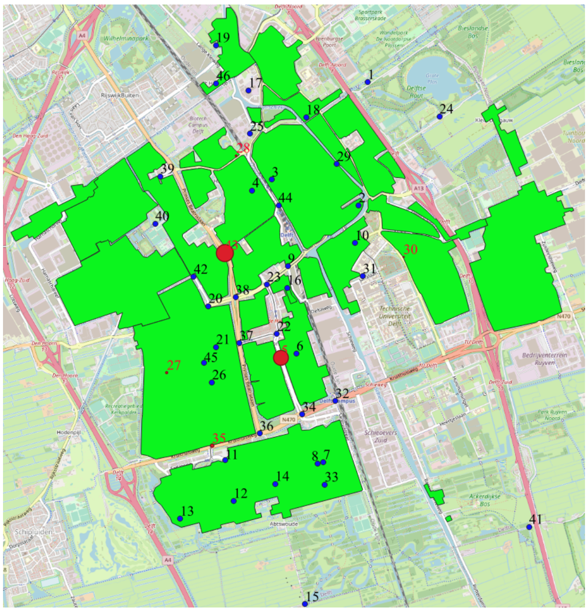


Figure 4.5.6 Scenario 4

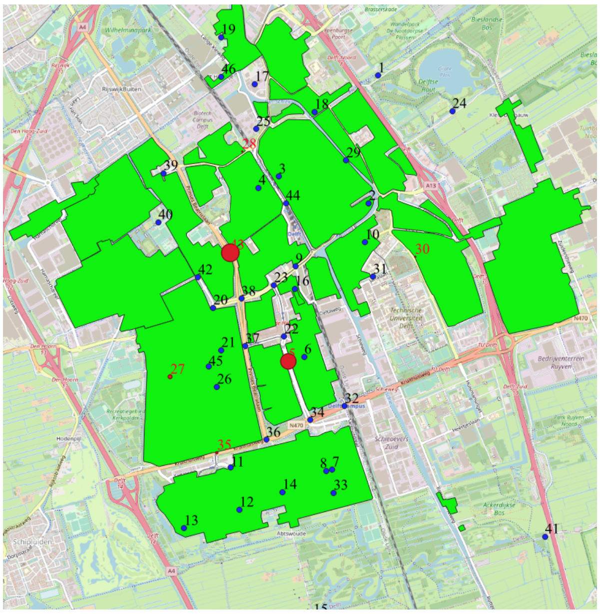


Figure 4.5.7 Scenario 5

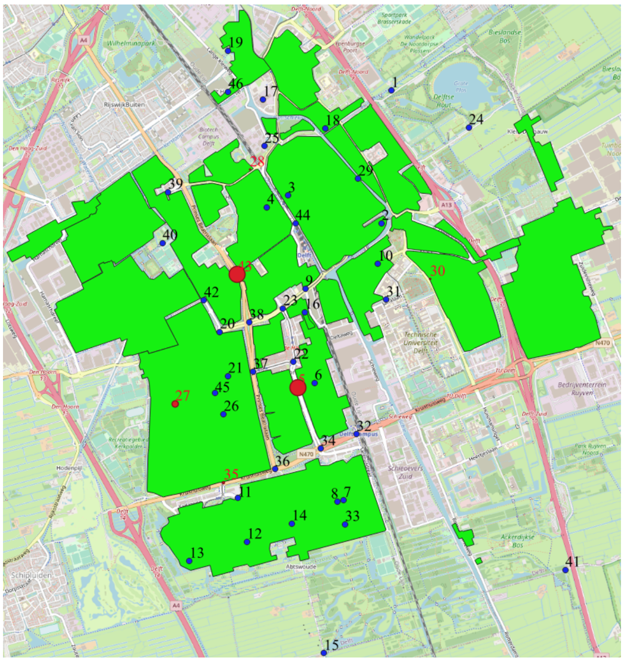


Figure 4.5.8 Scenario 6

From Figure 4.5.6, it is intuitionistic that the station size at Node 27 becomes much smaller than that in Scenario 1. Many demands that will be originally served at Node 27 are shifted to two stations at Node 5 and 43, which are outside the residential area.

With the relaxation of the limit, the station size at Node 27 increases a little bit compared to Scenario 4. Some demands that will be met at Node 35 in Scenario 4 will return to the station at Node 27. The service demands at Node 5 and 43 are not affected by the relaxation of the station size limit. This is because shifting demands from Node 35 to Node 27 will benefit the travel time more than from the other two nodes outside the residential area. In Scenario 6, it is more obvious that the station size at Node 27 becomes much larger than in the previous two scenarios, while the station size at Node 5 decreases because many demands return to Node 27 after further relaxing the station size limit.

In addition, the total construction cost in these three scenarios is also the same as that in Scenario 1, as well as *AC*. This is because the limit does not affect the total number of stations in the city in these three scenarios under this initial SOC set. In this case, the total construction cost will not change. However, it can be noticed that the demand distribution in the city will be significantly affected by the station size limit. In Scenario 1, there will be 1100 vehicles served in the residential area. After setting the station size limit, many demands are shifted out of the residential area. And the network travel time (*NTT*) and average travel time per vehicle (*ATT*) will become longer compared to Scenario 1 due to this demand shifting. This makes sense because the station size limits in these three scenarios are set on the basis of Scenario 1, which means that some vehicles will have to find different stations other than their original choices in Scenario 1 due to this compulsory limit. This will definitely lead to more detours in the traffic network. With the relaxation of the station size limit, the travel time will get better towards the value in Scenario 1. To visualize the effect of the station size limit on the construction cost compositions, demand distribution in the city, and the network travel time, two histograms and a scatter plot are exhibited in Figure 4.5.9, Figure 4.5.10, and Figure 4.5.11.

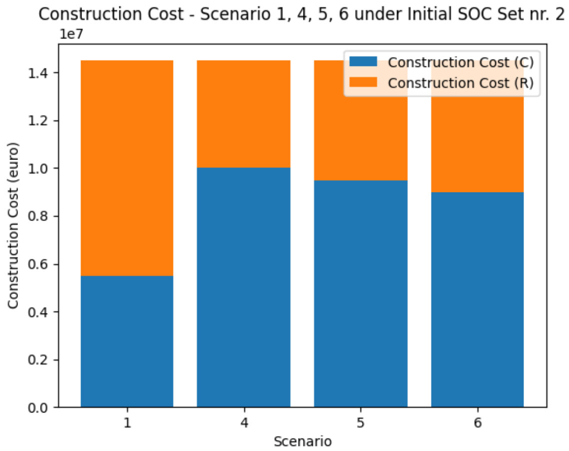


Figure 4.5.9 Construction cost

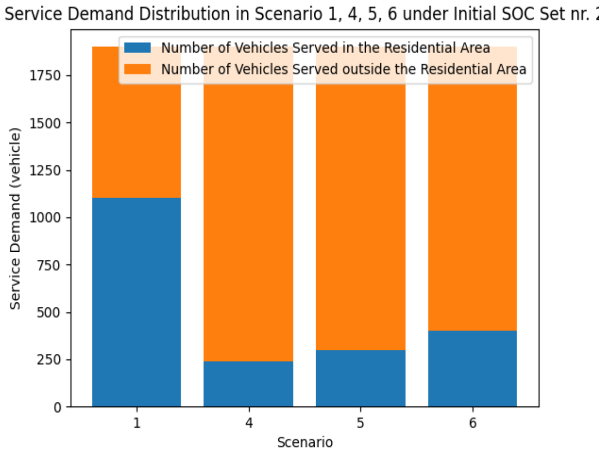


Figure 4.5.10 Service demand distribution

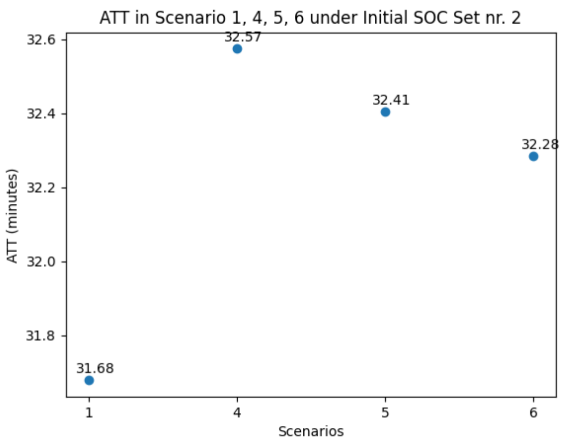


Figure 4.5.11 ATT

The experiment results obtained under the third and fourth random initial SOC sets again showed another possible situation that can be caused by setting the station size limit. In Scenario 4, the total construction cost might increase because the limit is too strict to meet the battery swapping demands of surrounding vehicles. More stations must be built to resolve all demands in the city, which will lead to a higher total construction cost.

To sum up, Scenario 4, 5, and 6 explore the impact of the station size limit on the location planning result, and Scenario 1 is considered as a base case for the comparison. The station size limit mainly has an impact on the construction cost compositions, demand distribution across the city, and network travel time. The total construction cost will not be definitely affected by the station size limit if the limit does not require new stations or change the number of stations inside and outside the residential area to meet all the battery swapping demands. However, if the limit is strict enough, there can still be a higher cost for meeting this limit. Besides, the same station size limit can have different impacts when the demand distribution in the city changes. The construction cost of stations in the residential area and the number of vehicles served in the residential area will be significantly influenced by the station size limit because the essence of setting such a limit is to shift demands from some places to other places. In these three scenarios, the goal is to shift battery swapping demands out of the residential area to guarantee acceptable livability there. By shifting demands, the route choices of some vehicles have to change compared to the base case, which means that there will be more or larger detours in the traffic network. Therefore, the network travel time and the average travel time per vehicle will be longer than the base case. The stricter the limit is, the more the travel time will be affected. And this indicates a potential trade-off between the living environment in the residential area and the traffic network performance. If someone wants to set an upper limit for the size of stations in the residential area to ensure a good living environment, one main "price" for this is to have more detours in the traffic network.

4.5.4 Impact of different optimization preferences – for better network travel time

This subsection will discuss the experiment result of Scenario 7, which will assign a weight of 3 to the travel time term in the objective function while all other settings keep the same as Scenario 1. It is expected that this scenario will output a better network travel time (*NTT*), as well as a better average travel time per vehicle (*ATT*).

From Table 4.5.4, it can be noticed that in Scenario 7, the locations of two stations are changed compared to Scenario 1. The station at Node 27 in Scenario 1 is moved to Node 14, and the station at Node 35 is moved to Node 45. The total number of stations does not change. However, there will be one more station constructed in the residential area compared to Scenario 1. The reason for this is that the residential land use in Delft takes up most of the area and they are centralized in the middle of the city. For many vehicles, they will have a smaller detour, thus a better travel time if they choose to pass a node in the residential area between origins and destinations than choosing a node outside the residential area. When the construction cost of stations in the residential area becomes less important than the travel time in the optimization, more stations will be located in the residential area to obtain a better travel time in the traffic network. In total, there will be 4 stations in the residential area in this case. The station locations in Scenario 7 are visualized in Figure 4.5.12. The sizes of stations in the residential area also become much larger than in Scenario 1. There will be 1500 vehicles served in the residential area. The network travel time decreases by 250 minutes for all 1900 vehicles while *AC* becomes 229.358 euros higher.

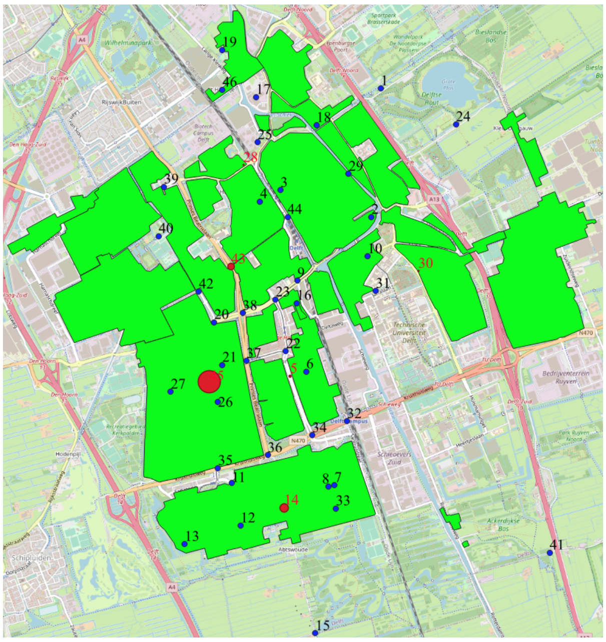


Figure 4.5.12 Scenario 7

The essence of assigning a weight to the travel time term in the objective function is to express the Willingness to Pay (WtP) of the decision-maker for reducing the network travel time compared to the base case. The heavier the weight is, the stronger the will for reducing the travel time is. After a weight is set in the objective function, a value of decision-maker's WtP is input into the model. The model will compare the "benefit" and the "cost" under this WtP and decide whether a new solution that is different from the base case should be output. In this case, the "benefit" for the decision-maker is the travel time reduction in the network (its economic effect), and the "cost" is the extra construction cost that needs to be paid to reach a better travel time. If the "benefit" can reach and exceed the "cost", a new solution will be considered worthwhile to be output, otherwise, the original case shall be kept, which means that the trade-off between the travel time and economic expenditure will be numerically solved by the model. This is an advantage of this model. Therefore, the model will not always provide new solutions under any WtPs. The decision-maker can clearly know whether a modification should be made to the original case by observing whether there is a new solution output by the model after he/she assigns a weight in the objective function. And there is no need to make decisions according to the personal subjective perceptions for the decision-maker.

To sum up, this subsection conducts comprehensive experiments on testing the impact of the preference for better network travel time on optimization. A common feature that can be identified in these three groups of experiments in Scenario 7 is that, in Delft, to obtain a better travel time in the network while considering constructing BSSs, it is inevitable that more stations shall be constructed in the residential area. This is due to the characteristic of the city's traffic network. From the map, it is intuitionistic that most of the lands are categorized as the residential land use type and most of these areas are located at the center of the city. In addition, by observing the trip data, it can be found that many origins and destinated are located in the residential area of the city, which means that it is quite possible that vehicles will have a better travel time if they swap their batteries inside the residential area because it will be a long distance if they have to drive to a node outside the residential area and then head back to their destinations. However, in this thesis, it is considered that constructing stations in the residential area will affect the livability level there. Therefore, this will be another critical trade-off for the decision-maker between the traffic network performance and the livability condition in the residential area of the city. Besides, whether the model will output a new solution with a better travel time compared to the base case is dependent on the decision-maker's WtP for the travel time reduction, which is reflected by the weight on the corresponding term in the objective function. And the model will not always provide a new solution every time the weight is adjusted. Only when the corresponding "benefit" for the decision-maker can exceed the "cost", there will be a new solution. Therefore, the model can automatically deal with the question that "whether a modification is worthwhile to be applied?" for the decision-maker. If there is a new solution other than the original case under a weight setting, the decision-maker can know it is worthwhile to make modifications, otherwise, no need for further modifications. Therefore, this model characteristic can provide critical inference for the decision-maker on the trade-offs between factors in the optimization.

4.5.5 Impact of different optimization preferences – for fewer/smaller stations in the residential area

This subsection will test Scenario 8 and see how the number of stations in the residential area will be affected by the optimization preference for fewer stations in the residential area.

From numerical results, it can be observed that Scenario 8 has exactly the same result as Scenario 4. This tells that assigning a weight to the construction cost of stations in the residential area finally leads to the same result as setting a strict station size limit. The number of stations in the residential area does not decrease as expected. Only the size of stations in the residential area is affected by this weight. To discover the deep reason for this, an auxiliary experiment is conducted. The weight on the construction cost of stations in the residential area is further increased in the objective function to check if heavier weights can lead to fewer stations in the residential area. The result turns out that the number of stations in the residential area will not decrease with the increasing weight. This indicates that three stations in the residential area are the smallest possible number in this case. Again, this is because of the existence of the service constraint in the model. None of these stations can be removed or relocated so that all demands can be met.

Although Scenario 8 has the same result as Scenario 4, there is still a significant difference between assigning a weight in the objective function and setting a station size limit. Assigning weight is a strategy that is applied in the objective function, which does not add any extra compulsory requirement to the model. This weight only indicates that the construction cost of stations in the residential area is more important than the other two factors in the objective function. However, the other two factors still play critical roles in the optimization. Besides, a heavy weight can guarantee that fewer or smaller stations will be built in the residential area compared to the base case because the construction cost in the residential are becomes quite important in the optimization. As for setting the station size limit, it is a compulsory requirement for the model. Setting a station size limit will add an extra constraint to the model, which must be met when solving the model. Therefore, the satisfaction of this constraint has the highest priority when doing the optimization. The construction cost (no matter inside or outside the residential area) and the travel time are all factors that can be "sacrificed" to meet this goal, which means that the station size limit only guarantees that smaller stations will be constructed at certain places. If the limit is extremely strict, it is possible that more stations will have to be constructed somewhere else, which will also lead to a higher construction cost. So, in general, the station size limit tends to have a stronger impact on the entire optimization.

The above analyses and illustrations can be proved by a small auxiliary experiment. If the weight on the construction cost of stations in the residential area is 1.5 in the objective function, instead of 3, the same result as Scenario 1 will be obtained. This proves that although the cost in the residential area becomes more important than the other two factors in the optimization, other factors are still influencing the final optimization result. And the model tells that other factors are not worthwhile to be sacrificed for obtaining a lower construction cost in the residential area with a weight of 1.5. Therefore, it can also be inferred that when the weight is in a "middle interval", which is not too small or too big, Scenario 8 probably can have a "middle" solution, which may not hugely affect the station size in the residential area like Scenario 4, and will also have a better travel time than Scenario 4, but worse than that in Scenario 1.

4.5.6 Impact of different optimization preferences – for less economic expenditure

This subsection will simulate an optimization preference that the decision-maker wants to lower the total economic expenditure on constructing BSSs in the network. Therefore, in the objective function, the weights on the construction cost of stations inside and outside the residential area are both increased to 3.

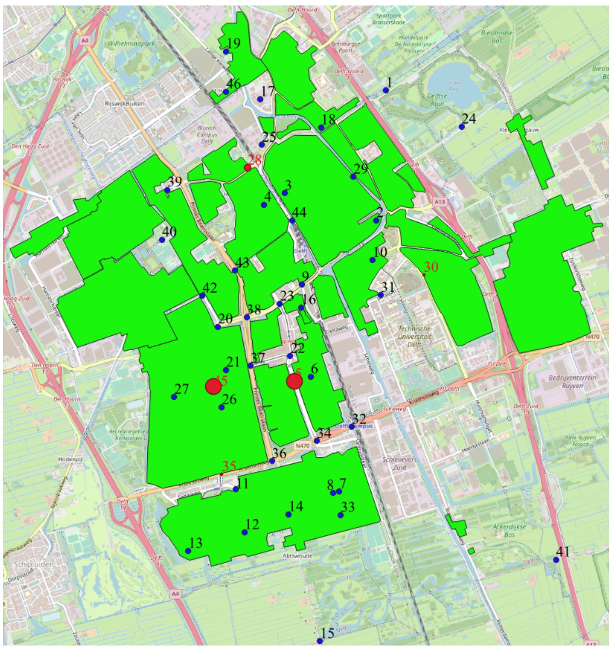


Figure 4.5.13 Scenario 9

From numerical results, it can be noticed that there are only five stations in total in Scenario 9, which is one station fewer than in Scenario 1, but there will still be three stations in the residential area. Station locations are visualized in Figure 4.5.13.

In this case, each station will serve 380 vehicles on average in a day. And the total construction cost is saved by 1,000,000 euros compared to Scenario 1. On average, 458.715 euros can be saved for each vehicle. However, this economic expenditure reduction is at a cost of a longer network travel time. From the standard deviation of travel time (*STD-TT*), it can be inferred that there will be a larger deviation among different individuals' travel time.

It was also found from experiments under other random SOC sets that a weight of 3 might not be enough to lead to a lower construction cost. However, as this weight was further increased, the expenditure can still be lowered down.

The result of this group of experiments shows that the total construction cost can be saved by reducing the number of stations and enlarging the size of some stations because the basic construction cost of a station is much more expensive than upgrading the size of an existing station. However, it is impossible that the number of stations can be permanently reduced to save more money. The spatial distribution of stations should still be able to satisfy all battery swapping demands in the city. Therefore, there will be a minimum possible number of stations in the network. If this number is reached, increasing the weight will not lead to fewer stations.

To sum up, assigning a heavy weight to the construction cost terms in the objective function is like an inverse of assigning a heavy weight to the travel time, namely, it is equivalent to lessening the weight of the travel time. This negative relative relation indicates the willingness of the decision-maker to achieve a better performance of a certain factor by sacrificing another one.

4.6 Summary of the case study

This case study explores what the location results will be under different random vehicle initial SOC sets, and tests nine different scenarios to discover what the impacts will be under different conditions and optimization strategies. The suggestions for Delft city on BSS location planning and the overall comment on each scenario will be summarized in this subsection.

4.6.1 BSS location planning suggestions for Delft

Subsection 4.5.1 specifically tested which nodes are most possible locations for building BSSs in Delft with and without the consideration of physical construction limit under multiple groups of random initial SOC sets.

When unsuitable nodes are excluded from candidate locations of the BSS, Node 5, 27, 28, and 43 are the four most possible locations for building BSSs in the city. Node 5 is on Pr. Beatrixlaan. Node 27 is in Buitenhof. Node 28 is on Kampveldweg. Node 43 is at the corner of the junction between Pr. Beatrixlaan and Westlandeweg.

It is also found that Node 3 is critical for meeting all battery swapping demands in the city. When the physical construction limit is relaxed for this node, the five most possible locations for building BSSs would become Node 3, Node 5, Node 27, Node 30, and Node 35. Node 3 is located near Delft Station. Node 30 is close to the junction between Schoemakerstraat and Kloosterkade. Node 35 is at the junction between Kruithuisweg and Buitenhofdreef.

These two groups of possible candidate locations are visualized in Figure 4.6.1 and Figure 4.6.2. Candidate locations (a) is the situation with physical construction limit everywhere. Candidate locations (b) is the situation with physical construction limit everywhere except for Node 3.

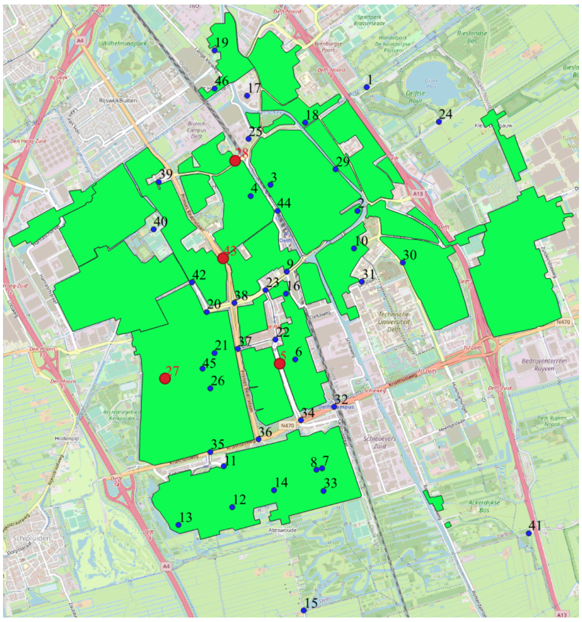


Figure 4.5.14 Candidate locations (a)

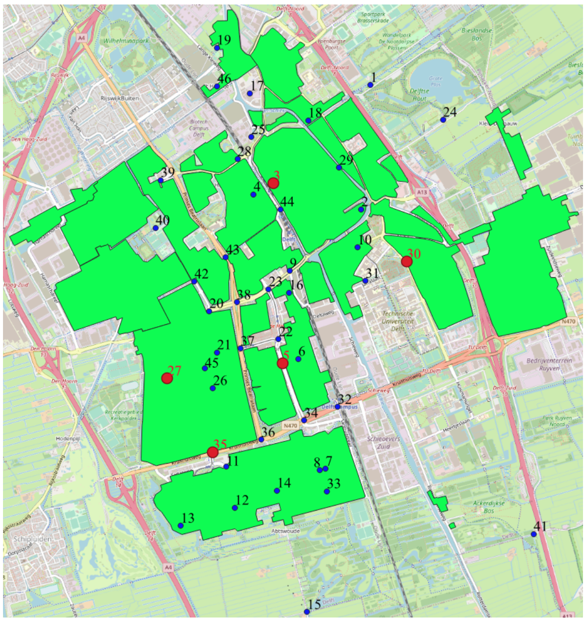


Figure 4.5.15 Candidate locations (b)

4.6.2 Overall conclusions of all scenarios

This case study explored nine scenarios to find out how the optimization can be influenced by the increasing EV traveling range, station size limit, and different optimization preferences. In this subsection, the answers to Sub-research question 4, 5, and 6 will be specifically concluded.

The uncertainty test proved that even if the initial SOC of the vehicle is full of randomness, there is still much certainty that can be found from optimal location results. Some meaningful suggestions can still be given to the city for making future plans.

Scenario 1, 2, and 3 simulated the impact of a growing EV traveling range on the optimal location decisions. The number, as well as the size of stations in the city, will both decrease in this case, along with an increasing average cost per vehicle, thus a worse investment cost performance. Therefore, the construction planning of this infrastructure should be made on a larger scale in the future to reach economies of scale. A larger scale network can include several cities and highway networks among them to capture the intercity battery swapping demands and behavior.

Scenario 4, 5, and 6 set three levels of station size limits in the residential area. This is an effective way to shift battery swapping demands out of the residential area to ensure that the size of stations there cannot be very large. However, the "price" is that there will be more detours in the city's traffic network, thus a longer travel time. Sometimes, more money shall be spent on station construction because of an over-strict limit, and it will lead to more stations in the city.

Scenario 7 proved that it is possible to reach a better traffic network performance by spending more money on station construction. Therefore, there exists a critical trade-off between the economic expenditure and the travel time in the city, which is directly related to the WtP of the decision-maker for the travel time reduction.

Scenario 8 indicated that the number of stations in the residential area might not be affected by the decision-maker's willingness due to the service constraint of the model, which regulates that all battery swapping demands in the city must be met. In this case, this willingness can finally lead to the same result as setting a strict station size limit. However, there still exist significant differences between these two ideas. A willingness to reduce the number of stations in the residential area is to tweak the weight of terms in the objective function, which still allows other concerns in the objective function to play their role and have an impact on the optimization while the station size limit has the highest priority to be met.

Scenario 9 is like an inverse experiment of Scenario 7, which proved that to a lower economic expenditure can be reached by tolerating a longer travel time in the city. This still indicates the trade-off between these two concerns.

5. Discussion

This these provides insight into the optimal locating problem of BSSs in the urban traffic network under a consideration for urban livability by developing an optimization model. The developed model is based on some existing models on solving the optimal locating problem of fuel stations and charging stations and is adapted to the research goal of this thesis. In this research, urban livability is related to urban residents' living environment and EV drivers' travel time because the construction and operation of BSSs can cause much noise and increase the safety risk in the residential area in the city, and influence the travel time of EVs that intend to swap batteries during their trips. Therefore, the developed model focuses on balancing the interests of different stakeholders in BSS's locating problem, including system investors, urban residents, and system users (EV drivers) so that urban livability plays a role in the optimization, and making it realistic for the decision-maker to apply their personal optimization preferences for three stakeholders. This section will discuss the main findings of this research, implications for the decision-maker, research limitations, and recommendations for future research.

5.1 Research findings

The main findings of this research can be generally summarized into two aspects – an integrated optimization model for solving the locating problem of BSSs and the impacts of optimization strategies and possible future scenarios on urban livability.

The developed optimization model integrates the interests of three stakeholders into one objective function by evaluating all concerns in monetary units. It has been illustrated in Section 2 that a bi-level structure can cause the risk that the lower-level objective can be over-constrained by the upper-level objective and as a result, dominated by the upper-level objective (Zang et al. (2018)). The multi-objective model has no interactions or correlations between different objectives, thus can hardly capture the trade-offs between them. However, these problems can be resolved by combining multiple concerns in one single objective function in a linear form with multiple decision variables. This structure requires the model to make several decisions simultaneously so that different concerns in the objective function can have impact on each other. In addition, it is convenient for the decision-maker to apply different preferences under various possible situations, which increases the possibility and diversity of the optimization.

In the case study of this research, it is found that various optimization strategies and possible future scenarios can have impacts on urban livability, though some of their intentions are not to do so. Through the experiments, it is observed that as the maximum traveling range of the EV increases, the battery swapping demands in the city will decrease. This decrease in demand will then to a reduction in the total number of BSSs required in the city, as well as a corresponding decrease in the station sizes. However, predicting the impact on the number of BSSs in residential areas and the total travel time in the traffic network proved challenging due to the changing distribution characteristics of battery swapping demands under different EV maximum traveling ranges.

In addition to evaluating the impact of the EVs maximum traveling range on battery swapping demands and BSS locations, the effects of implementing a station size limit, particularly in residential areas, are also examined in experiments. The station size limit was designed to ensure that the construction and operation of BSSs did not adversely affect the livability level in the residential area. And it is revealed that when the station size limit was relatively "flexible", the size of BSSs in residential areas decreases, while the number of BSSs remains unchanged. This result shows an improvement in the livability levels of the residential area, as the smaller stations are less likely to affect urban residents' daily lives. However, when the station size limit becomes excessively strict, such that the battery swapping demands in the city cannot be completely met, additional stations are needed in this case. The locations of these extra stations can either be within or outside the residential areas. Under this circumstance, the strict limit will have a potential negative impact on the livability levels of the residential areas due to increased construction activity. Furthermore, the travel time in the traffic network was significantly affected as some vehicles had to navigate larger detours to access the BSSs complying with the size limit.

The impact of a preference for better travel time on urban livability is found to be closely related to the city's land use feature. For example, Delft is a city in which residential land use takes up most areas. Under this condition, emphasizing the importance of travel time has the potential to affect the livability level in the residential area because vehicles are more possible to experience smaller detours if choosing stations located there than choosing those located in other areas. Therefore, a conflict exists between obtaining a better travel time and guaranteeing the livability level in the residential area. Conversely, when residential land use occupies a smaller proportion of the city s overall area, emphasizing the significance of travel time in the optimization process can have a different effect. In this scenario, the preference for better travel times might further discourage the construction of BSSs in residential areas. As a result, the livability level in the residential area can improve due to the absence of BSS-related activities, promoting a quieter and safer environment for urban residents.

The fourth factor examined in experiments is the preference for reducing the number (and the size) of stations in the residential area. To apply this preference, a heavy weight is assigned to the construction cost of BSSs in residential areas in the objective function. However, the number of stations in the residential area does not decrease as anticipated. This unexpected outcome can be caused by the service constraint in the developed model. Therefore, even with a preference for fewer stations in the residential area, the optimization process still requires a sufficient number of stations to effectively serve all demands, that is, the number of stations in the residential area will not permanently decrease as the corresponding weight increases in the objective function. Furthermore, when the assigned weight becomes excessively heavy, it will make the construction cost in the residential area dominate the optimization, which means that the construction cost outside the residential area and the travel time will not influence the decision-making anymore, and this preference might yield same solutions as those obtained by implementing a station size limit.

The last factor tested in this research is a preference for spending less money on station construction. From experiments, it is found that the total number of stations in the city will decrease under this preference. However, the number of stations in the residential area will not be necessarily influenced. Since emphasizing the importance of the total economic expenditure in the optimization implicitly indicates that the importance of traffic network performance is becoming less important and it can have a worse performance if more money can be saved for constructing stations, the travel time is always affected, which can even become much worse than that when implementing the strictest station size limit. Therefore, it can be concluded that the livability level in the residential area of the city may not be influenced by a preference for less economic expenditure, but EV drivers are quite easy to be affected by this preference.

5.2 Implications of the research

This research also provides strong implications for the decision-maker of BSS's locating problem. In general, there are four aspects of implications – recommendations for making future planning, differences between similar optimization strategies, possible inferences from the model output, and possible trade-offs that can be met.

The experiments done in Scenario 1, 2, and 3 in Section 4 indicate that as the EV's traveling range becomes wider and wider, the battery swapping demands that can be identified in a city will rapidly decrease. In this research, the widest traveling range of the EV is only set to be 300 km, which is shorter than the actual range of many EVs in the world. When the maximum traveling range is 300 km, there will only be about 240 vehicles that need to swap batteries during their next trips. Although this number is quite small for a city, they are still distributed at various places, which means that to get all of them served, sometimes it is not enough to build only one station in the city. The more they are decentralized, it is more possible that many stations need to be built. In this case, the service density per station per day can be extremely small, which will significantly affect the efficiency of the investment. Therefore, when considering about the optimal location decision of BSSs in the future, it is better to make planning on a large-scale network, such as a regional traffic network that includes several cities and highway networks among them. By this means, more battery swapping demands can be planned at the same time. The inefficiency brought by investing in those small stations can be eliminated by constructing many other big stations. In addition, when the traveling range of the EV is wide enough, it is more possible that many vehicles will choose to swap batteries when they are traveling between cities on the highway network, so making planning on a regional level can help to capture the traffic interactions among different cities and the battery swapping behavior on highway networks.

The second implication of this research is about the difference between different optimization strategies. Some optimization strategies can have many features in common, and can even lead to the same optimization result, for example, implementing a station size limit in the residential area and emphasizing the importance of the construction cost of stations in the residential area. Both the two optimization strategies are to guarantee the livability level in the residential area of the city. And it is also found that they are likely to lead to the same optimization result. However, there is still a significant difference between them. And they will have quite different impacts on other performance indicators. Compared to implementing a station size limit, emphasizing the importance of construction cost of stations in the residential area is a "milder" method for ensuring an acceptable living environment in the residential area. It tends to protect the performance of other indicators at the same time, while a station size limit is actually an extra constraint for the optimization that must be met when solving the model. In this case, all other indicators can perform worse than the original case to keep this extra constraint held. For the decision-maker, it is critical to be aware of this kind of differences, which is helpful for determining which strategy should be selected under a certain goal. If the decision-maker thinks other performance indicators should still play a role in the optimization, it is better to assigning a weight to the construction cost in the objective function, and this weight is supposed to be adjusted slowly to avoid causing dominations. On the other hand, if enhancing the living environment in the residential area is the absolute first goal for the decision-maker, it is better to directly set a station size limit there.

The third implication of this research is about the characteristics of the developed model. In the case study, it can be noticed that when practicing some preferences, the model would not produce a new solution other than the base solution as expected, that is, sometimes the model is not sensitive to some changes in the optimization. For the decision-maker, much information can be inferred from the "sensitive interval" of the model. Figure 5.2.1 exhibits these kinds of information:

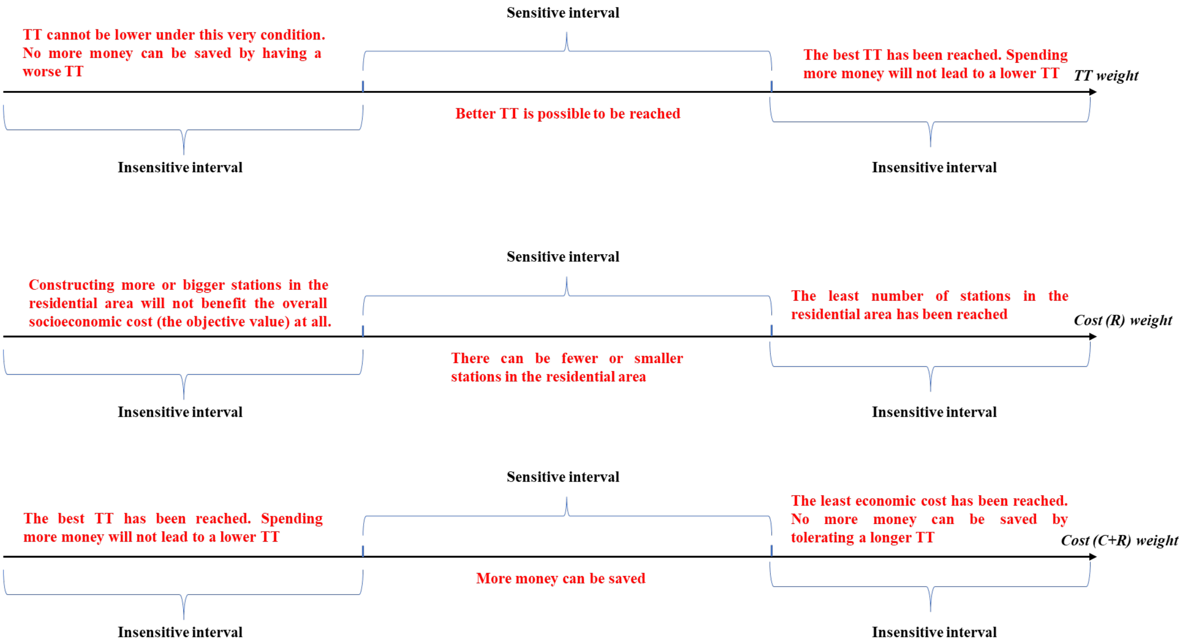


Figure 5.2.1 Sensitive and insensitive intervals of the model under different weight settings

When changing the weight of the network travel time term, if the model begins to be insensitive to the increasing weight, one can infer that the best network travel time has been reached under the identified demands in the previous solution. And spending more money will not lead to a better travel time in this case. If the model begins to be insensitive to the decreasing weight, one can infer that the network travel time cannot be worse, and no more money can be saved by having a worse travel time.

When changing the weight of the construction cost in the residential area, if the model begins to be insensitive to the increasing weight, one can infer that the least number of stations and the smallest size of stations in the residential area have been reached. This part of cost cannot be less if all demands must be met by station's spatial distribution. If the model begins to be insensitive to decreasing weight, one can infer that constructing more or larger stations in the residential area will not benefit the construction cost outside the residential area or the network travel time anymore.

When changing the weight of the total construction cost, if the model begins to be insensitive to the increasing weight, one can infer that the possible least economic cost has been reached in the previous solution. No more money can be saved by tolerating a longer network travel time. If the model begins to be insensitive to the decreasing weight, one can infer that the best network travel time has been reached by the previous solution, and spending more money cannot lead to a better network travel time.

The last implication of this research is a summary of all possible trade-offs that can be faced by the decision-maker when considering about the optimal locating problem of BSSs. 1) The trade-off between theoretical planning and real construction. In Section 4, it is found that Node 3 in Delft is critical for serving all battery swapping demands in the city. However, the physical surrounding environment of Node 3 is quite unsuitable for constructing a BSS because it is densely surrounded by a railway station, a river, some retail shops, some residential houses, and some office buildings. Building a BSS there can hugely affect these surrounding elements. Part of the street will need to be replanned and reconstructed. If exclude Node 3 from candidate locations of BSSs in this city, it is likely that some vehicles will fail to find a station to swap their batteries before their batteries run out of power. 2) The trade-off between the traffic network performance and the livability in the residential area when implementing the station size limit and under the preference for a better travel time. It has been demonstrated in Section 4 and Section 5.1 that the station size limit in the residential area will always affect the total travel time in the traffic network as this limit can cause more detours in the city. Under this condition, better livability can be reached by a station size limit but meanwhile, sacrifices the experience of EV drivers in the traffic network. For cities in which residential land use occupies most of the areas, practicing a preference for better travel time in the traffic network may also cause a conflict between the travel time and the livability in the residential area. 3) The trade-off between the traffic network performance and the economic expenditure on station construction. From experiments in this research, it can be found that to obtain a better travel time than the base solution, more money shall be spent on station construction due to the requirement for more or larger stations. On the contrary, the travel time will be greatly affected if the decision-maker wants to save more money when constructing stations.

5.3 Research limitations and recommendations for future research

Although the developed model is able to make determinations for optimal decision-making on the BSS's locating problem, there are still many simplifications and limitations for this model. This subsection will summarize all these limitations and make recommendations accordingly.

First, the static traffic network is a huge simplification of traffic status, which can have a significant impact on the traffic assignment result. Therefore, the station choice result of the vehicle derived from the current model may have a large deviation from the real situation. In future research, it is recommended to apply the BPR function to precisely calculate the link travel time related to the vehicle's route choice and take the congestion effect into consideration. Second, the vehicle's waiting time at a station would not always be a fixed constant. This is also an element that can affect a vehicle's station choice in reality. It is better to incorporate the queuing theory into the model to capture the queuing effect at a station and make the result of the vehicle's station choice more accurate. Third, the BCS is totally ignored in this thesis, so the battery swapping demands may be overestimated in this model. In future research, considering the charging behavior may better predict daily battery swapping demands. The next point is about the intra-node travel time. In reality, there will always be a certain distance between the vehicle and the BSS instead of a distance of 0. The service constraint should be further modified as well when considering a non-zero intra-node travel time. The relationship between the station size and the corresponding construction cost is a bit vague. A more precise mathematical relationship should be determined in the future. Furthermore, the current model simply assumes that the service capacity of each station is infinite, regardless of batteries' usage, and does not track the charging schedule of batteries at each station, that is, the time horizon it omitted in the current model. Vehicles can move to any station as they want. This gives too much freedom to the prediction of the vehicle's station choice. If battery dynamics can be taken into account, the vehicle's station choice result would be closer to its true condition.

6. Conclusions

In the final section of this thesis, answers to all the research questions will be formulated first, and this section will also reflect on the scientific and societal contributions of this research.

6.1 Answers to research questions

In this subsection, answers to all research questions, including two sub-questions and one main research question will be formulated. The two sub-questions will be answered first, and then the main research question will be generally discussed based on the answers of two sub-questions.

Sub-question 1: Which stakeholders should be considered in the optimization?

In this thesis, the developed model considers interests of three stakeholders – BSS system investors, urban residents, and EV drivers. It is expected that this model is able to produce balanced optimal solution with concerns about the economic investment, livability condition in the residential area, and the traffic network performance. The urban resident is a stakeholder that is completely missed in existing research on the optimal locating problem of the BSS, so it is considered as a parallel stakeholder to the other two.

Sub-question 2: How to quantitatively evaluate all stakeholders' interests in the model?

Sub-question 3: How to make the model flexible for decision-makers so that they can apply personal preferences to the optimization?

Sub-research question 2 and 3 shall be answered together. In Subsection 2.3, many modeling methodologies that focused on simultaneously considering multiple objectives or concerns in the optimization were studied. Based on the knowledge of this, this thesis finally chose to formulate a model with one single objective function that contains all three stakeholders' interests in it with a linear form. The advantage of this model structure is that it is easy to solve and is flexible for the decision-maker to apply personal optimization preferences to the model. The requirement of this structure is to unify the evaluation measurement of all factors in the objective function. Therefore, this thesis research chose to convert all concerns into the monetary unit. VoT is used to convert the temporal unit into monetary unit. Urban residents' concerns are converted into a "penalty" cost in station construction expenditure. If a station will be constructed in the residential area of the city, more money must be spent to mitigate its possible negative impact on livability. By this means, all three stakeholders' concerns can be evaluated under the same measurement. Besides, the economic investment and economic effect of the travel time is also evaluated on the same time scale by incorporating the lifespan of the BSS into the model. The depreciation cost per day of the station can be calculated in this case. With this general structure and interest evaluation strategy, the decision-maker is able to apply personal optimization preferences to the model by tweaking the weight of terms in the objective function.

Sub-research question 4: How will the increasing traveling range of the EV influence optimal decision-making?

This sub-research question describes a possible future situation when considering about the optimal locating problem of the BSS in urban areas. Through experiments in Scenario 1, 2, and 3, it was found that the increasing EV traveling range will lead to the reduction of daily battery swapping demands in the city. As a result, the required number of BSSs in the city will reduce as well. Overall, the total station construction cost will decrease, but the cost performance of the investment will be greatly reduced because the average investment cost per vehicle will be greatly increased. The average number of vehicles that will be served by each station in a day is much fewer than when daily battery swapping demand is high.

Sub-research question 5: How will a station size limit in the residential area influence optimal decision-making?

To ensure good livability in the residential area of the city, it is possible for the decision-maker to set a station size limit there to control the negative impact of the station on residents' living. It was found that this limit will greatly increase the station size outside the residential area. And the travel time will be affected compared to the situation that has no limit because more vehicles have to detour due to this limit. The total station construction cost will not be necessarily affected. More money is needed only when the limit is so strict that more stations are required to be built to meet all battery swapping demands in the city. In general, a station size limit is a compulsory requirement for the optimization, like an extra constraint for the model. To meet this constraint, every other factor in the optimization can be "sacrificed" no matter how bad their performance would be. Therefore, when considering applying this limit, the decision-maker should be cautious about its strictness.

Sub-research question 6: How will different optimization preferences influence optimal decision-making?

This sub-research question focuses on trade-offs among three stakeholders' concerns. Three different preferences were tested in the case study part of this thesis. The first preference was to obtain a better travel time, so a heavy weight was assigned to the travel time term in the objective function. It was found that there existed a critical trade-off between the travel time and the station construction cost. To reach a better travel time, more money shall be spent. For the city of Delft, the size of stations in the residential area would become larger as well to reach a better travel time in the traffic network. Therefore, the Willingness to Pay of the decision-maker for the travel time reduction plays a critical role in this trade-off.

The second preference was to construct fewer stations in the residential area, so a heavy weight was assigned to the construction cost of stations in the residential area in the objective function. In experiments conducted in this thesis, this preference did not lead to fewer stations in the residential area as expected because of the existence of the service constraint. As a result, this preference finally had the same result as setting a station size limit. However, applying this preference to the optimization still has a significant difference from setting a station size limit. This preference will have a milder impact on other factors because this is not a compulsory constraint for the model. The construction cost of stations outside the residential area and the travel time can still influence the optimal decision-making under this preference.

The last preference tested in this thesis is to spend less money on station construction. This preference is like an inverse of reaching a better travel time. Spending less money is to tolerate a longer travel time in the traffic network, which is also equivalent to assigning a small weight to the travel time term in the objective function. And it was found that the number of stations would reduce under this preference. Those demands that were originally met by two or more stations would be converged to one station in this case. Therefore, some of the stations would become quite large under this circumstance.

Main research question: How can an optimization model be constructed and applied to determine the best Battery Swapping Station locations in the urban traffic network, considering its impact on urban livability?

On the basis of the answers to the six sub-research questions, an overall conclusion can be drawn to answer the main research question.

The model simultaneously considers the interests of BSS system investors, urban residents, and EV drivers so that the correlations and interactions among these stakeholders can be captured by the model. In this case, the derived optimal solution is a balanced solution. BSS's negative impact on urban livability is incorporated into the model by considering urban residents' resistance to the BSS near their houses. Three concerns are evaluated under a unified measurement, organized in a linear form within a single objective function. The objective function minimizes the overall negative effects for all three stakeholders to determine the optimal locations for the BSS in the city. Alternative optimal solutions can be obtained by tweaking the weight on different terms in the objective function, which is able to indicate specific preferences of the decision-maker. The main constraint of the model is that all battery swapping demands identified in the city must be met.

6.2 Reflections

This section will make some reflections on the scientific and societal contributions of the findings of this thesis.

6.2.1 Scientific contributions

In Section 2.3 of this thesis, a literature review highlighting the state-of-the-art in terms of modeling the locating problem of BSSs and BCSs is presented. The strengths and weaknesses of existing methodologies are also summarized in the review. And a research gap is identified that there is no model considering urban residents as a critical stakeholder in the optimal locating problem of BSSs, so the impact of BSSs on urban livability is missed in existing scientific research. In addition, these current studies do not consider multiple possibilities of optimization under various possible situations.

This research has developed a model that can be used to determine the optimal spatial distribution of BSSs in the urban traffic network with consideration for assuring an acceptable urban livability level so that the identified research gap can be filled with this model. The construction cost of the BSS is divided into two categories based on whether the station is located in the residential area. For those that are built in the residential area, the system investors must pay an extra cost to mitigate their negative impacts on the living environments. By this means, the utility of building a station in the residential area can be naturally limited in the optimization. This also helps to express the depreciation of urban residents to a BSS near their houses. Meanwhile, the construction cost of stations outside the residential area and the travel time in the traffic network are two parallel concerns in the objective function, so the developed model is in a relatively balanced state because the three concerns equally play their roles in the optimization, which increases the feasibility in the real world of the optimal solution derived from this model.

In addition to a balanced optimization model, the case study part of this research also examines the impact of various possible situations on optimization. The potential uncertainty brought by the randomness of vehicles' initial SOC sets is specifically tested and suggested locations for building BSSs in the city are chosen by observing multiple groups of optimal solutions to make sure that they will not be biased by the randomness under a certain initial SOC set. Furthermore, the conflict between theoretical planning and real construction is also found in this part of the experiments, which is a critical trade-off for the decision-maker to face in the future.

The nine scenarios in the case study explore the potential impacts of technology development in the EV field, a compulsory measurement for guaranteeing a good living environment in the residential area, and three possible preferences that the decision-maker can have on optimal decision-making. Abundant evaluation indicators are designed to comprehensively estimate the influence of different decision modes on optimization. The experiment results of these nine scenarios can be used by the decision-maker as a basis for a more in-depth analysis of trade-offs among a series of indicators. And this is helpful for forming a comprehensive view of the entire optimization.

6.2.2 Societal contribution

In Section 2.1, it has been illustrated that the EV is an important new traffic mode in the urban traffic mobility system. It is meaningful to make plans for completely incorporating this new mode into the traffic network, and infrastructure planning is one of the most critical problems to be solved in this case. This planning can help to reduce range anxiety and increase the penetration rate of EVs. By efficiently locating BSSs in the urban area, more individuals will be willing to transition to EVs, leading to a reduction in fossil fuel consumption and mitigating the environmental impact of transportation. Besides, since the developed model specifically pays attention to urban residents and EV drivers, the produced optimal solution can better balance the interests of different stakeholders instead of only emphasizing the interests of investors and operators, which enhances the social equity in this problem. Meanwhile, the confidence of the system investors can still be guaranteed. Although it is necessary to pay more attention to residents and drivers, investors play a pivotal role in the deployment of the BSS system. Ensuring their interests are considered in the decision-making process is crucial for attracting private capital and achieving widespread BSS implementation. Therefore, suggestions on how to achieve more efficient investment are also formulated in this research. To sum up, the optimization model for solving the locating problem of BSSs represents a significant societal contribution towards promoting sustainable urban mobility, fostering investor confidence, enhancing accessibility of new infrastructures and social equity, and reducing range anxiety to accelerate the EV's further promotion in the future.

References

Ahmad, F., Saad Alam, M., Saad Alsaidan, I., & Shariff, S. M. (2020). Battery swapping station for electric vehicles: opportunities and challenges. *IET Smart Grid*, *3*(3), 280-286.

Andersson, H. (2007). Willingness to pay for road safety and estimates of the risk of death: evidence from a Swedish contingent valuation study. *Accident Analysis & Prevention*, *39*(4), 853-865.

Agrawal, M., & Rajapatel, M. S. (2020). Global perspective on electric vehicle 2020. *International Journal of Engineering Research & Technology*, *9*(1), 8-11.

Byaruhanga, C. B., & Evdorides, H. (2021). A systematic review of road safety investment appraisal models. *Cogent Engineering*, *8*(1), 1993521.

Cao, Y., Tang, S., Li, C., Zhang, P., Tan, Y., Zhang, Z., & Li, J. (2011). An optimized EV charging model considering TOU price and SOC curve. *IEEE Transactions on Smart Grid*, *3*(1), 388-393.

Cui, D., Wang, Z., Liu, P., Wang, S., Dorrell, D. G., Li, X., & Zhan, W. (2022). Operation optimization approaches of electric vehicle battery swapping and charging station: A literature review. *Energy*, 126095.

D'Alessandro, F., Di Mascio, P., Lombardi, L., & Ridolfi, B. (2021). Methodology for the identification of economic, environmental and health criteria for road noise mitigation. *Noise Mapping*, *9*(1), 10-22.

Dincer, I., & Acar, C. (2015). A review on clean energy solutions for better sustainability. *International Journal of Energy Research*, *39*(5), 585-606.

Ecola, L., Batorsky, B., & Ringel, J. S. (2015). *Using Cost-Effectiveness Analysis to Prioritize Spending on Traffic Safety*. Rand Corporation.

Feng, Y., & Lu, X. (2021). Construction planning and operation of battery swapping stations for electric vehicles: a literature review. *Energies*, *14*(24), 8202.

Ferro, G., Minciardi, R., Parodi, L., & Robba, M. (2020). Optimal planning of charging stations and electric vehicles traffic assignment: a bi-level approach. *IFAC-PapersOnLine*, *53*(2), 13275-13280.

Goldszmidt, A., List, J. A., Metcalfe, R. D., Muir, I., Smith, V. K., & Wang, J. (2020). *The value of time in the United States: Estimates from nationwide natural field experiments* (No. w28208). National Bureau of Economic Research.

Hertzke, P., Müller, N., Schenk, S., & Wu, T. (2018). The global electric-vehicle market is amped up and on the rise. *McKinsey Cent. Futur. Mobil*, *1*, 1-8.

Lam, T. C., & Small, K. A. (2001). The value of time and reliability: measurement from a value pricing experiment. *Transportation Research Part E: Logistics and Transportation Review*, *37*(2-3), 231-251.

Li, J., Liu, C., Wang, Y., Chen, R., & Xu, X. (2023). Bi-level programming model approach for electric vehicle charging stations considering user charging costs. *Electric Power Systems Research*, *214*, 108889.

Li, J., Liu, Z., & Wang, X. (2022). Public charging station localization and route planning of electric vehicles considering the operational strategy: A bi-level optimizing approach. *Sustainable Cities and Society*, *87*, 104153.

Li, K., Shao, C., Hu, Z., & Shahidehpour, M. (2022). An MILP Method for Optimal Planning of Electric Vehicle Charging Stations in Coordinated Urban Power and Transportation Networks. *IEEE Transactions on Power Systems*.

Lin, B., & Wu, W. (2021). The impact of electric vehicle penetration: A recursive dynamic CGE analysis of China. *Energy economics*, *94*, 105086.

Lindgren, S. (2021). A sound investment? Traffic noise mitigation and property values. *Journal of Environmental Economics and Policy*, *10*(4), 428-445.

Miralinaghi, M., Lou, Y., Keskin, B. B., Zarrinmehr, A., & Shabanpour, R. (2017). Refueling station location problem with traffic deviation considering route choice and demand uncertainty. *International Journal of Hydrogen Energy*, *42*(5), 3335-3351.

Mon, E. E., Jomnonkwao, S., Khampirat, B., Satiennam, W., & Ratanavaraha, V. (2018). Willingness to pay for mortality risk reduction for traffic accidents in Myanmar. *Accident Analysis & Prevention*, *118*, 18-28.

Noori, M., & Tatari, O. (2016). Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. *Energy*, *96*, 215-230.

Svensson, M., & Johansson, M. V. (2010). Willingness to pay for private and public road safety in stated preference studies: why the difference?. *Accident Analysis & Prevention*, *42*(4), 1205-1212.

Thota, M., & Wang, K. W. (2017). Reconfigurable origami sonic barriers with tunable bandgaps for traffic noise mitigation. *Journal of Applied Physics*, *122*(15).

Tu, H., Feng, H., Srdic, S., & Lukic, S. (2019). Extreme fast charging of electric vehicles: A technology overview. *IEEE Transactions on Transportation Electrification*, *5*(4), 861-878.

Wang, Z., Luo, D., & Huang, Z. (2009). Integration control for traffic corridors considering guidance information. *Journal of Control Theory and Applications*, *7*, 445-453.

Wu, H. (2021). A survey of battery swapping stations for electric vehicles: Operation modes and decision scenarios. *IEEE Transactions on Intelligent Transportation Systems*, *23*(8), 10163-10185.

Xi, X., Sioshansi, R., & Marano, V. (2013). Simulation–optimization model for location of a public electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment*, *22*, 60-69.

Yang, S., Yao, J., Kang, T., & Zhu, X. (2014). Dynamic operation model of the battery swapping station for EV (electric vehicle) in electricity market. *Energy*, *65*, 544-549.

Zang, H., Fu, Y., Chen, M., Shen, H., Miao, L., Zhang, S., ... & Sun, G. (2018). Bi-level planning model of charging stations considering the coupling relationship between charging stations and travel route. *Applied Sciences*, *8*(7), 1130.

Zhan, W., Wang, Z., Zhang, L., Liu, P., Cui, D., & Dorrell, D. G. (2022). A review of siting, sizing, optimal scheduling, and cost-benefit analysis for battery swapping stations. *Energy*, 124723.

Zhang, B., Zhao, M., & Hu, X. (2023). Location planning of electric vehicle charging station with users' preferences and waiting time: multi-objective bi-level programming model and HNSGA-II algorithm. *International Journal of Production Research*, *61*(5), 1394-1423.

Zhang, Y., Wang, Y., Li, F., Wu, B., Chiang, Y. Y., & Zhang, X. (2020). Efficient deployment of electric vehicle charging infrastructure: Simultaneous optimization of charging station placement and charging pile assignment. *IEEE Transactions on Intelligent Transportation Systems*, *22*(10), 6654-6659.

Appendix A. Datasets of the toy network

Table A.1 Node set

Node	***Inside/Outside residential areas?***
1	IN
2	IN
3	OUT
4	OUT
5	OUT
6	OUT

Table A.2 Link (weight) set

Link number	***Initial node***	***End node***	***Travel time***
1	1	2	6
2	1	5	3
3	2	5	5
4	2	6	2
5	3	5	1
6	3	6	3
7	4	5	5
8	5	6	4
9	2	1	6
10	5	1	3
11	5	2	5
12	6	2	2
13	5	3	1

14	6	3	3
15	5	4	5
16	6	5	4

Table A.3 OD matrix

	1	***2***	***3***	***4***	***5***	***6***
1	-	20	50	33	42	64
2	6	-	68	34	56	77
3	40	20	-	30	20	60
4	24	36	65	-	70	80
5	43	26	35	15	-	45
6	27	39	13	61	72	-

Table A.4 Shortest path length

	1	***2***	***3***	***4***	***5***	***6***
1	0	6	4	8	3	7
2	6	0	5	10	1	2
3	4	5	0	6	1	3
4	8	10	6	0	5	9
5	3	5	1	5	0	4
6	7	2	3	9	4	0

Appendix B Experiment results of the case study

Table B.1 Overall numerical results of nine scenarios (under the third random initial SOC set)

Scenario	***Station locations***	***C_c (euro)***	***C_r (euro)***	***S_{dense}***	***NTT (min)***	***ATT (min)***	***STD-TT (min)***
1	[5, 9, 27, 28, 30, 35, 43]	9,000,000	7,000,000	306	66,590	31.117	4.179
2	[38, 45]	2,000,000	2,500,000	300	21,000	35.000	0.061
3	[27, 43]	1,500,000	1,500,000	180	9,800	35.543	0.213
4	[5, 9, 20, 27, 28, 30, 35, 43]	12,000,000	4,500,000	268	67,780	31.673	4.093
5	[5, 9, 27, 28, 30, 35, 43]	10,500,000	5,500,000	306	67,630	31.603	4.169
6	[5, 9, 27, 28, 30, 35, 43]	10,000,000	6,000,000	306	67,590	31.584	4.179
7	[5, 9, 27, 28, 30, 35, 43]	9,000,000	7,000,000	306	66,590	31.117	4.179
8	[5, 9, 20, 27, 28, 30, 35, 43]	12,000,000	4,500,000	268	67,780	31.673	4.093
9	[5, 26, 28, 30, 43]	7,500,000	7,500,000	428	68,030	31.790	4.492

Continued Table B.1

Scenario	N_{sta}	N_r	D_c	D_r	***Demand distribution***	***Total construction cost (euro)***	***AC (euro)***
1	7	3	1,360	780	[700, 100, 500, 80, 200, 60, 500]	16,000,000	7476.636
2	2	1	300	300	[300, 300]	4,500,000	7500.000
3	2	1	180	100	[100, 180]	3,000,000	10714.290
4	8	3	1,860	280	[780, 200, 100, 100, 80, 100, 80, 700]	16,500,000	7710.280
5	7	3	1,660	480	[780, 100, 200, 80, 200, 80, 700]	16,000,000	7476.636
6	7	3	1,560	580	[700, 100, 300, 80, 200, 60, 700]	16,000,000	7476.636
7	7	3	1,360	780	[100, 380, 60, 60, 300, 1000]	16,000,000	7476.636
8	8	3	1,860	280	[780, 200, 100, 100, 80, 100, 80, 700]	16,500,000	7710.280
9	5	3	1,300	840	[600, 460, 180, 200, 700]	15,000,000	7009.346

Table B.2 Overall numerical results of nine scenarios (under the fourth random initial SOC set)

Scenario	***Station locations***	***C_c (euro)***	***C_r (euro)***	***S_{dense}***	***NTT (min)***	***ATT (min)***	***STD-TT (min)***
1	[2, 5, 13, 27, 28, 43]	3,500,000	13,500,000	387	71,350	30.754	3.917
2	[9, 27]	1,000,000	3,500,000	270	19,340	35.815	1.991
3	[27, 28]	0	3,500,000	130	9,460	36.385	2.631
4	[5, 9, 14, 20, 27, 28, 30]	11,500,000	6,000,000	332	72,650	31.315	3.977
5	[5, 9, 14, 20, 27, 28, 30]	10,000,000	7,500,000	332	72,400	31.207	4.047
6	[5, 12, 27, 28, 30, 43]	9,500,000	8,000,000	332	72,130	31.091	4.017
7	[2, 5, 9, 14, 27, 28, 43]	4,500,000	13,500,000	332	70,790	30.513	3.895
8	[5, 9, 14, 20, 27, 28, 30]	11,500,000	6,000,000	332	72,650	31.315	3.977
9	[2, 5, 13, 27, 28, 43]	3,500,000	13,500,000	387	71,350	30.754	3.917

Continued Table B.2

Scenario	N_{sta}	N_r	D_c	D_r	***Demand distribution***	***Total construction cost (euro)***	***AC (euro)***
1	6	4	540	1,780	[380, 240, 400, 900, 100, 300]	17,000,000	7327.586
2	2	1	80	460	[80, 460]	4,500,000	8333.333
3	2	2	0	260	[200, 60]	3,500,000	13461.540
4	7	4	1,980	340	[700, 400, 100, 880, 100, 40, 100]	17,500,000	7543.103
5	7	4	1,680	640	[580, 300, 200, 800, 200, 40, 200]	17,500,000	7543.103
6	6	4	1,660	720	[540, 300, 300, 180, 300, 700]	17,000,000	7327.586
7	7	4	520	1,800	[380, 140, 80, 400, 1000, 20, 300]	18,000,000	7758.621
8	7	4	1,980	340	[700, 400, 100, 880, 100, 40, 100]	17,500,000	7543.103
9	6	4	540	1,780	[380, 240, 400, 900, 100, 300]	17,000,000	7327.586