ΕΘΝΙΚΟ ΜΕΤΣΟΒΙΟ ΠΟΛΥΤΕΧΝΕΙΟ
Σχολή Ηλεκτρολόγων Μηχανικών και Μηχανικών Υπολογιστών
Διατμηματικό Πρόγραμμα Μεταπτυχιακών Σπουδών
«Παραγωγή και Διαχείριση Ενέργειας»
Ηρώων Πολυτεχνείου 9, 157 73, Ζωγράφου – 210-7723655 – epminfo@power.ece.ntua.gr

ΜΕΤΑΠΤΥΧΙΑΚΗ ΕΡΓΑΣΙΑ

«Βέλτιστος σχεδιασμός σημείων φόρτισης για στόλους ηλεκτρικών οχημάτων εμπορευματικών μεταφορών»

Της Μεταπτυχιακής Φοιτήτριας

Δημητρίου Παρασκευής

Επιβλέπων

Γκιοτσαλίτης Κωνσταντίνος
Επίκουρος Καθηγητής
Τμήμα Πολιτικών Μηχανικών ΕΜΠ

Αθήνα, Οκτώβριος 2023

ΕΘΝΙΚΟ ΜΕΤΣΟΒΙΟ ΠΟΛΥΤΕΧΝΕΙΟ
Σχολή Ηλεκτρολόγων Μηχανικών και Μηχανικών Υπολογιστών
Διατμηματικό Πρόγραμμα Μεταπτυχιακών Σπουδών
«Παραγωγή και Διαχείριση Ενέργειας»
Ηρώων Πολυτεχνείου 9, 157 73, Ζωγράφου – 210-7723655 – epminfo@power.ece.ntua.gr

Post-Graduate Thesis

« Optimal Planning of charging stations for fleets of electric vehicles in urban freight transport »

Student
Dimitriou Paraskevi

Supervisor
Gkiotsalitis Konstantinos
Assistant Professor
School of Civil Engineering NTUA

Athens, October 2023

Εγκρίθηκε από τα Μέλη της Τριμελούς Εξεταστικής Επιτροπής:

Πρώτος Εξεταστής (Επιβλέπων)	Δρ. Γκιοτσαλίτης Κωνσταντίνος Επίκουρος Καθηγητής, Σχολή Πολιτικών Μηχανικών, Εθνικό Μετσόβιο Πολυτεχνείο
Δεύτερος Εξεταστής	Δρ. Ριζιώτης Βασίλειος Αναπληρωτής Καθηγητής, Σχολή Μηχανολόγων Μηχανικών, Εθνικό Μετσόβιο Πολυτεχνείο
Τρίτος Εξεταστής	Δρ. Καρώνης Δημήτριος Καθηγητής, Σχολή Χημικών Μηχανικών Εθνικό Μετσόβιο Πολυτεχνείο

Ευχαριστίες

Ευχαριστώ θερμά τον επιβλέποντα καθηγητή Δρ. Γκιοτσαλίτη Κωνσταντίνο για τη συνεργασία, την καθοδήγηση και τις συμβουλές του, στην εκπόνηση της παρούσας διπλωματικής εργασίας, την Δρ. Νικολοπούλου Αμαλία, για την πολύτιμη βοήθειά της, καθώς και τους καθηγητές Δρ. Ριζιώτη Βασίλειος και Δρ. Καρώνη Δημήτριο, μέλη της Τριμελούς Εξεταστικής Επιτροπής.
Επιπλέον, θα ήθελα να ευχαριστήσω τον μέντορά μου Γιώργο, για την στήριξή του επαγγελματικά και ψυχολογικά τα τελευταία χρόνια.

Περιεχόμενα

POST-GRADUATE THESIS:	**«Optimal Planning of charging stations for fleets of electric vehicles in urban freight transport »**
STUDENT:	**Dimitriou Paraskevi**
SUPERVISOR:	**Gkiotsalitis Konstantinos, Assistant Professor, School of Civil Engineering NTUA**
ACADEMIC YEAR:	**2022-2023**

Abstract

The necessity to reduce emissions in the transport sector has led to the advancement of electromobility. Nowadays, electromobility is developing rapidly in the urban freight transport sector. This helps to reduce the environmental footprint of transport, given the large portion of emissions that originate from the freight transport sector. However, the use of electric vehicle fleets for freight transport has some limitations, such as autonomy, charging delays, and lack of charging infrastructure. In this study, we focus on the problem of finding the optimal locations for charging stations of freight transport vehicles in the urban network. The installation of charging stations is a major issue, as it is necessary to identify the optimal locations of installation points in order to improve the delivery of products and reduce the empty vehicle kilometers driven for charging purposes. This study formulates the charging station location selection problem aiming at minimizing the empty kilometers driven to reach the charging stations, taking into consideration the destinations of truck deliveries. The developed model is an Integer Linear Program (ILP) that can be effectively solved to global optimality for realistic problem instances. Further, this study employs sensitivity analysis to identify specific factors with significant impact on the selected locations of charging stations. Experiments are performed using benchmark instances demonstrating the scalability of our approach and the sensitivity of our solutions to the changes of different factors.

Summary

Nowadays, the urban freight transport sector is evolving rapidly and impressively as climate change intensifies, and increased concerns about air quality promote the transition to more sustainable forms of alternative transportation. In this context, the development of electrification has emerged as one of the key solutions to reduce greenhouse gas emissions and improve air quality. However, the optimal functionality of electric vehicles in the urban freight transport sector depends to a large extent on the existence and efficiency of charging infrastructure.

Undoubtedly, in the 21st century, freight transportation faces significant challenges. Given the population growth and concentration in large urban centers, there is an increase in the demand for goods and distribution services. However, high levels of air pollution emissions, noise pollution, and traffic congestion hinder the optimal transportation planning. Based on all the above, the transition from conventional vehicles (with internal combustion engines) to electric vehicles is a one-way path for transportation and distribution companies. Electric vehicles are environmentally friendly, have better performance, are more cost-effective, and contribute to noise reduction. However, this transition requires strategic planning and a significant background of charging infrastructure networks to be sustainable.

The development of electric vehicle charging infrastructure is a crucial step towards sustainable mobility. The selection of the optimal location is a research problem in transportation science as it contributes to the efficiency, accessibility, and efficiency of charging infrastructure. When selecting a location, multiple parameters are taken into account, such as the geographical distribution of demand, public accessibility, specific needs and constraints of the local community, and economic factors. The analysis of the optimal locations of electric vehicle charging stations also requires the consideration of different types of loads (fast charging, regular charging, etc.) and different user categories, including individuals, businesses, communities with stationary charging needs, and designated areas.

In this work, the importance of the optimal planning of charging infrastructure on the urban network is examined with the aim of serving the consumers (level of satisfaction). In addition, the main factors contributing to location selection, such as demand, cost, and station capacity, are analyzed. By developing an integer linear programming model, the best locations are found through a series of scenarios.

To assess the model's effectiveness, sensitivity analysis was conducted to examine the influence and importance of factors such as station capacity, proximity and budget in solving the model. It is evident that station capacity significantly affects the solution in relation to proximity and budget.

ΜΕΤΑΠΤΥΧΙΑΚΗ ΕΡΓΑΣΙΑ: **«Βέλτιστος Σχεδιασμός Σημείων φόρτισης για Στόλους Ηλεκτρικών Οχημάτων Εμπορευματικών Μεταφορών»**

ΦΟΙΤΗΤΗΣ: **Δημητρίου Παρασκευή**

ΕΠΙΒΛΕΠΩΝ: **Γκιοτσαλίτης Κωνσταντίνος, Επικ. Καθηγητής,**

Τμήμα Πολιτικών Μηχανικών ΕΜΠ

ΑΚΑΔΗΜΑΪΚΟ ΕΤΟΣ: **2022-2023**

Σύνοψη

Η ανάγκη για τη μείωση των εκπομπών στον τομέα των μεταφορών οδήγησε στην ανάπτυξη νέων βιώσιμων και πράσινων πρακτικών. Η ηλεκτροκίνηση θεωρείται μια από τις αναδυόμενες τάσεις της εποχής και αναπτύσσεται ραγδαία στον τομέα των αστικών εμπορευματικών μεταφορών. Αυτό συμβάλλει στη μείωση της περιβαλλοντικής επιβάρυνσης των μεταφορών, λαμβάνοντας υπόψη το μεγάλο ποσοστό των εκπομπών που προέρχονται από τον τομέα των εμπορευματικών μεταφορών. Ωστόσο, η χρήση ηλεκτρικών φορτηγών για τις αστικές μεταφορές έχει ορισμένους περιορισμούς, όπως η αυτονομία, οι καθυστερήσεις φόρτισης και η έλλειψη υποδομών φόρτισης. Σε αυτήν τη μελέτη, επικεντρωνόμαστε στο πρόβλημα εύρεσης των βέλτιστων τοποθεσιών για τους σταθμούς φόρτισης για χρήση οχημάτων εμπορευματικών μεταφορών στο αστικό δίκτυο. Η εγκατάσταση των σταθμών φόρτισης αποτελεί καίριο ζήτημα, καθώς είναι απαραίτητο να εντοπιστούν οι βέλτιστες τοποθεσίες εγκατάστασης για τη βελτίωση της παράδοσης προϊόντων και τη μείωση των νεκρών χρόνων και χιλιομέτρων του οχήματος, που διανύονται για σκοπούς φόρτισης. Η μελέτη αυτή διατυπώνει το πρόβλημα επιλογής τοποθεσίας σταθμού φόρτισης με στόχο την ελαχιστοποίηση των κενών χιλιομέτρων προς τους σταθμούς φόρτισης, λαμβάνοντας υπόψη τους προορισμούς των φορτηγών. Το μοντέλο που αναπτύσσεται είναι ένα μοντέλο ακέραιου γραμμικού προγραμματισμού (ILP) που μπορεί να επιλυθεί αποτελεσματικά κάνοντας χρήση και δοκιμές σε ρεαλιστικές περιπτώσεις προβλημάτων (ρεαλιστικά δεδομένα). Επιπλέον, πραγματοποιείται ανάλυση ευαισθησίας για τον καθορισμό των παραγόντων εκείνων οι οποίοι είναι οι πιο σημαντικοί στη διαμόρφωση της βέλτιστης λύσης. Συγκεκριμένα, εξετάζεται η επίδραση της χωρητικότητας των σταθμών φόρτισης, του διαθέσιμου κεφαλαίου καθώς και της αποδεκτής απόστασης που καλείται ο οδηγός να καλύψει για να φορτίσει το όχημά του, στη βέλτιστη επιλογή σταθμών φόρτισης. Για το σκοπό αυτό διεξάγονται εκτενή υπολογιστικά πειράματα πάνω σε νέα, τροποποιημένα πρότυπα προβλήματα της βιβλιογραφίας τα οποία αναδεικνύουν την αποτελεσματικότητα του μοντέλου επίλυσης σε μεσαίας και μεγάλης κλίμακας προβλήματα.

Περίληψη

Στις μέρες ο τομέας των αστικών εμπορευματικών μεταφορών εξελίσσεται με ραγδαίο και εντυπωσιακό ρυθμό, καθώς η κλιματική αλλαγή εντείνεται και οι αυξημένες ανησυχίες για την ποιότητα του αέρα προωθούν τη μετάβαση σε πιο βιώσιμες μορφές και εναλλακτικές μεταφορές. Στο πλαίσιο αυτό, η ανάπτυξη της ηλεκτροκίνησης έχει αναδειχθεί ως μία από τις βασικές λύσεις για την μείωση των εκπομπών αερίων θερμοκηπίου και την βελτίωση της ποιότητας του αέρα. Ωστόσο, η βέλτιστη λειτουργικότητα των ηλεκτρικών οχημάτων στον τομέα των αστικών εμπορευματικών μεταφορών εξαρτάται σε μεγάλο βαθμό από την ύπαρξη και την αποτελεσματικότητα των υποδομών φόρτισης.

Αναμφίβολα, τον 21ο αιώνα οι εμπορευματικές μεταφορές αντιμετωπίζουν μεγάλες προκλήσεις. Δεδομένης της αύξησης και της συγκέντρωσης του πληθυσμού στα μεγάλα αστικά κέντρα, παρατηρείται αύξηση στη ζήτηση αγαθών και στις υπηρεσίες διανομής. Όμως, οι μεγάλες ποσότητες εκπομπών αέριων ρύπων, η ηχορύπανση και η κυκλοφοριακή συμφόρηση, δυσχεραίνουν το βέλτιστο σχεδιασμό των μεταφορών. Βάσει όλων των παραπάνω, η μετάβαση των συμβατικών οχημάτων (με κινητήρες εσωτερικής καύσης) σε ηλεκτρικά οχήματα, αποτελεί μονόδρομο για τις εταιρείες μεταφορών και διανομών αγαθών. Τα ηλεκτρικά οχήματα αποτελούν μέσο κίνησης, φιλικό προς το περιβάλλον, έχουν καλύτερη απόδοση, είναι πιο οικονομικά, ενώ συμβάλλουν και στη μείωση του θορύβου. Ωστόσο, αυτή η μετάβαση απαιτεί στρατηγικό σχεδιασμό και ένα σημαντικό υπόβαθρο υποδομής δικτύων φόρτισης για να είναι βιώσιμη.

Η ανάπτυξη υποδομών φόρτισης ηλεκτρικών οχημάτων αποτελεί καίρια ενέργεια μετάβασης προς την κατεύθυνση της βιώσιμης κινητικότητας. Η επιλογή της βέλτιστης τοποθεσίας αποτελεί πρόβλημα μελέτης για την επιστήμη των μεταφορών, καθώς συμβάλλει στην αποτελεσματικότητα, την προσβασιμότητα και την αποδοτικότητα της υποδομής φόρτισης. Κατά την επιλογή τοποθεσίας λαμβάνονται υπόψη πολυάριθμες παράμετροι, όπως η γεωγραφική κατανομή της ζήτησης, η πρόσβαση του κοινού, οι ειδικές ανάγκες και περιορισμοί της τοπικής κοινότητας, και οι οικονομικοί παράγοντες. Η ανάλυση της βέλτιστης τοποθεσίας σταθμών φόρτισης ηλεκτρικών οχημάτων απαιτεί επίσης τη συνεκτίμηση των διαφόρων τύπων φορτίου (γρήγορη φόρτιση, κανονική φόρτιση κλπ.) και των διαφορετικών κατηγοριών χρηστών, όπως ιδιώτες, επιχειρήσεις, κοινότητες με ανάγκες σταθερής φόρτισης, αλλά και ταξινομημένες περιοχές.

Στην παρούσα διπλωματική εργασία, εξετάζεται το πρόβλημα της βέλτιστης επιλογής τοποθεσίας υποδομών φόρτισης σε δίκτυα μεταφορών, με σκοπό την μείωση της συνολικά διανυόμενης απόστασης (κόστους) των ηλεκτροκίνητων οχημάτων. Για το σκοπό αυτό, αναπτύσσεται μοντέλο ακέραιου γραμμικού προγραμματισμού, μέσω του οποίου επιτυγχάνεται η εύρεση των βέλτιστων τοποθεσιών, για μια σειρά σεναρίων. Για την εξέταση της αποτελεσματικότητας του προτεινόμενου μοντέλου δημιουργήθηκαν νέα, τροποποιημένα πρότυπα προβλήματα της βιβλιογραφίας. Επιπλέον, αναλύονται οι κύριοι παράγοντες που συμβάλλουν στην επιλογή της βέλτιστης τοποθεσίας, όπως η χωρητικότητα των σταθμών φόρτισης, το διαθέσιμο κεφάλαιο καθώς και η αποδεκτή απόσταση που καλείται ο οδηγός να καλύψει για να φορτίσει το όχημά του. Τα υπολογιστικά πειράματα καταδεικνύουν ότι η χωρητικότητα του σταθμού φόρτισης επηρεάζει σημαντικά τη βέλτιστη λύση των υπό εξέταση προβλημάτων.

1 Introduction

One of the biggest issues of the 21st century is the global warming due to the excessive greenhouse gas emissions [1]. Although the advancement of new technologies aims to reduce the greenhouse gas emissions, particularly CO_2, approximately one-quarter of these emissions come from the transportation sector [2]. More specifically, in 2017 it was recorded that 27% of the total greenhouse gas emissions in the European Union came from transportation. Furthermore, it was noted that from 1990 there has been an increase of over 25%, with further increases expected in the future, primarily from the freight transport sector [1]. Based on the above, the adoption of green applications and practices has become necessary to make freight transport more sustainable in terms of economic, societal, and environmental aspects [3].

One of the big changes of our time is electrification (e-mobility), and particularly the use of electric battery-powered fleets for last-mile deliveries (Electric Freight Vehicles) [4]. According to research conducted in 2010, the growing population and the rapid growth in freight transport are expected to contribute to a 77% increase in general transportation by 2055 [5–11]. Given this, the development and adoption of electric vehicles is expected to play a crucial role in achieving very low emissions, reducing noise, and improving air quality in major urban centers. Although the use of electric fleets in freight transport has numerous advantages, the lack of charging infrastructure is one of the main concerns for businesses that are exploring the convention of their fleets from conventional to electric vehicles. As a consequence, the functional integration of electrification into the field of freight transport is postponed.

Taking into consideration all the above, the strategic installation of charging stations in "key" locations becomes essential to support long-distance deliveries. The optimal design and placement of charging stations is necessary to ensure autonomy, efficiency, sufficiency in freight transport operations, and minimization of the final operational cost. It should be emphasized that the optimal location selection of charging stations is needed to reduce the cost of electricity provision and charging times (delays-queue) [12]. Given that, the decision of location selection is crucial for the efficient functioning of a charging station, and considering that there are limited financial resources available for the construction of infrastructure, it is necessary select optimally the locations of charging stations in the urban network. This will help to limit the potential negative effects of charging station installation, such as environmental, economic, and social impacts, while contributing to increased levels of final customer's satisfaction.

The optimal location of a charging station is determined by various factors, including the type of technology used for the station, the drivers' behavior, the charging time, the installation cost, the travel time to the charging station, and the traffic network [13]. Installing charging infrastructure in the road network is a critical decision because the utilization rate of a public electric vehicle charging station is a key factor in determining its efficiency and effectiveness. The necessity of optimal placement is highlighted in many studies, which show that the utilization rates of existing charging stations are low, indicating poor/inappropriate location choices [14–16]. Furthermore, the rapid increase in the simultaneous use of multiple electric vehicles poses a significant challenge for the energy sector. It necessitates the development of appropriate charging infrastructure, the creation of the required network conditions, and the advancement of technology [17].

Based on all the previous information provided, it becomes evident that existing electric vehicle charging infrastructure is typically inadequate to cover the needs of freight transport. The utilization of existing electric vehicle charging stations has significant impacts on both road traffic (traffic congestion) and energy consumption, while potentially causing voltage drop issues within the network. This highlights the shortcomings of the charging station location choices in urban areas. Specifically, in many areas with such installations there is a burden on the transport network due to vehicle overload, leading to increased delays and reduced parking space availability [18]. Additionally, energy consumption rises in certain areas due to simultaneous charging, resulting in difficulties in power supply and potential issues such as transformer overloads, imbalances in phase, and voltage deviations. In light of these challenges, it is essential to carefully plan the location and distribution of electric vehicle charging stations, taking into account factors such as the network capacity, the traffic flow, and the energy demand to ensure their optimal functionality and minimize the negative impacts on both transportation and energy systems [16, 19–21]. Undoubtedly, the need for the development of fast, reliable, and user-friendly technologies would facilitate freight transport operators in the practical use of electric vehicles, promote green transportation practices, and reduce the dependency of distribution on fossil fuel sources [22, 23].

The aim of this thesis is to find the optimal locations for installing charging stations for urban freight transport in a given area, with the primary criterion being the service level improvement and the reduction of empty kilometers driven for charging purposes. More specifically, the constraints encountered during the creation of a charging station will be analyzed and presented, such as economic limitations, routing constraints, and placement within the road network. Precisely determining the coordinates of the most suitable locations for charging station installation requires special attention to factors such as the charging technology, charging time, type of electric vehicle, and the availability of charging infrastructure. Based on all of the above, a design model is created that optimally selects the locations for charging station installation, with an emphasis on freight vehicles.

The remainder of the thesis is structured as follows. The second section consists of the literature review, which involves the review of past studies that have addressed the classic Facility Location Problem (FLP). The aim is to gather information and mathematical models developed to solve the problem of optimal placement of electric charging stations in the urban network, considering the constraints in their design and operation, as well as any applications that have been implemented to evaluate their effectiveness in freight transportation. Gaps in the existing literature are identified by creating summary tables to consolidate all the research conducted on the problem of optimal placement, focusing on areas that require improvement. In the third section, the methodology is analyzed and an integer linear program for the charging station location selection problem for urban freight transport is developed. The proposed model is analyzed and it is tested in numerical experiments in section four. The model is programmed in Python and it is solved with Gurobi. To assess the effectiveness of the model, a case study is conducted in a defined area. In the fifth section, the conclusions of the analysis are presented, highlighting potential areas for future research.

2 Literature Review

2.1 Charging Technologies

The rapid increase of environmental pollution has led to the advancement of electrification. This marks the path towards gradual decarbonization and independence of transportation from fossil fuels [13, 24]. Electric vehicles are one of the emerging trends, as electrification is one of the most sustainable and environmentally friendly approaches. Electric vehicles significantly contribute to the reduction of CO2 emissions, and therefore, to the mitigation of the greenhouse effect [25]. They also contribute to reducing noise levels in large urban centers [26]. However, the rapid integration of electric vehicles into urban areas is challenging due to the lack of charging infrastructure, specifically charging stations' availability. The smooth integration of electrification into freight transportation poses a significant challenge in today's context. While the goal is to reduce emissions, there are many constraints that make the conversion of distribution fleets from conventional to electric vehicles difficult, thus hindering the improvement of the end consumer's service level.

In transportation, the constraints faced by electric vehicle providers primarily relate to the vehicles' battery range and the availability of electric vehicle charging infrastructure along their routes. Many cities and communities have started to recognize the benefits of electrification, and there is willingness to improve the planning of charging stations in order to promote the use of electric vehicles [27, 28]. Therefore, the decision-making process for the optimal location selection of new charging stations within a city is crucial. The Charging Station Location Problem (CSLP) involves a set of constraints that need to be defined and satisfied when selecting the most appropriate installation points. The most important aspects that are typically taken into consideration are the following [29]:

Charger Utilization: Charging stations for electric vehicles are categorized into three (3) basic levels, each of which determines their technical specifications and final cost, according to [30]. Specifically, for residential use, Level 1 chargers are recommended, which are typically slow-charging installations. For work and public use in parking lots, hotels, supermarkets, etc., Level 2 installations are recommended, which are usually fast-charging stations. Level 3 chargers are primarily recommended for locations such as highways and fuel stations. The different characteristics of each charging level are illustrated in Fig.1.

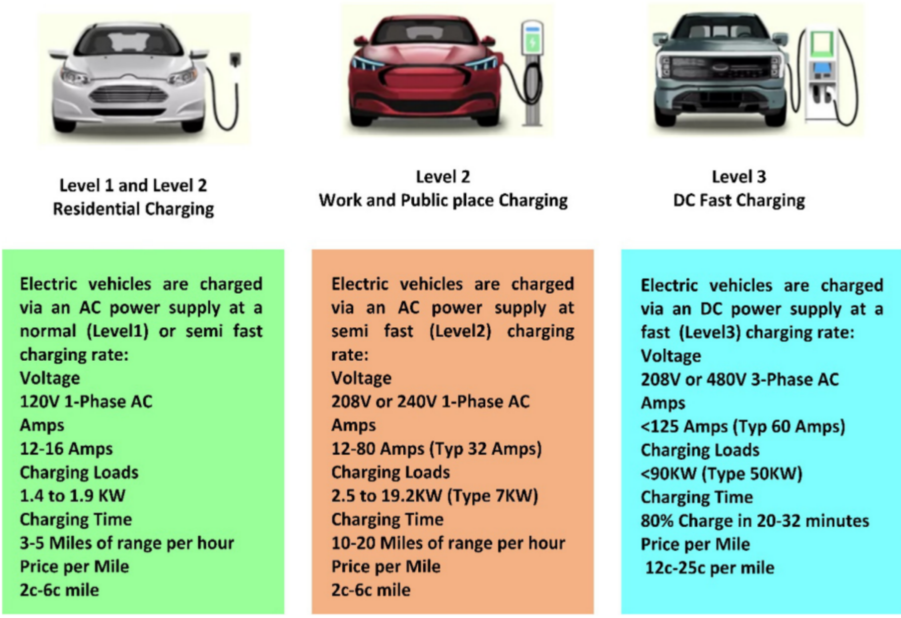

Fig. 1 Charger utilization per level [31]

Charger Types: The types of chargers at electric charging station installations are divided into two categories: direct current (DC) chargers and alternating current (AC) chargers. Specifically, DC chargers allow for the direct charging of the vehicle, as opposed to alternating current (AC), which is present in the grid and needs to be converted into DC in order to be adapted in electric vehicle batteries. As a result, the charging process is much faster since the step of converting from AC to DC is skipped [32, 33].

Charging Technologies: Starting with the types of charging stations, advancements in technology and expertise in the field of electrification have led to the development of various new charging station technologies aimed at enhancing user convenience. According to the literature, emerging charging station technologies include:

- Conductive Charging: Conductive charging offers several advantages, including its economic feasibility, fast charging capability, user-friendly operation, and high efficiency. In addition to this, conductive charging has been further classified into two categories[34]. Onboard chargers, such as AC-DC converters, are typically slow chargers designed to charge the vehicle entirely within. On the contrary, offboard chargers are known for their rapid charging capabilities. Furthermore, using offboard chargers can also enhance the electric vehicle's range by reducing the vehicle's weight[35]. In the following, two types of conductive charging are presented.

Overnight Depot Charging: Overnight depot charging facilities provide both fast and slow charging options, with the charging point typically located at the end of designated lines. These facilities are primarily used for overnight charging, taking advantage of the minimal impact on the distribution grid. Slow charging is the most advantageous choice in this context[36] [37]. However, for applications necessitating high battery capacity and quick recharging, the Pantograph charging technique is more suitable.

Pantograph Charging: Pantograph charging offers a range of charging options and is commonly employed for applications requiring greater battery capacity and power, such as buses and trucks. This charging approach reduces the investment required for bus batteries but increases infrastructure costs[38].

- Fast Charging: This method allows electric vehicles to charge as quickly as possible compared to conventional plug-in methods. Fast charging reduces the battery recharging wait time, making it more practical for drivers and distributors [39]. Fast charging stations can be categorized into DC (direct current) stations, which connect to direct current, and ultra-fast charging stations, which achieve even faster charging levels but require high voltage levels in the grid. However, it's important to note that the charging time depends not only on the type of charger but also on factors such as battery size (capacity) and the charger's power capacity for recharging batteries. In Greece, for example, the most common capacity for fast chargers ranges from 50-150 kilowatts (kw). In a fast charging station, an electric vehicle's battery can be charged from 0% to 80% within 45 minutes. The last 20% for a full charge takes longer because the system slows [40].
- Battery swapping: This is an alternative technology that allows users to replace their depleted electric vehicle battery with a fully charged one, whether it's new or recharged. This technology may potentially increase waiting times, as access to a battery swapping station is required, and it takes some time to perform the battery swap. According to [29, 41], a Battery Swapping Station (BSS) can slow down the charging process, resulting in an extended battery lifespan. Forms of renewable energy sources, such as solar and wind power generated from the local grid, can be integrated into the BSS system [31, 42].
- Inductive Charging: Inductive charging is a wireless charging technology that allows electric vehicles to charge without the need for a physical connection between the vehicle and the charging infrastructure. Through the presence of an electromagnetic field, electrical energy is transferred between the vehicle's pole and the charging infrastructure [43, 44]
- Dynamic Charging: Similar to inductive technology, but in this case, it allows for the charging of moving vehicles. This method requires the installation of charging infrastructure on the road surface or overhead, enabling wireless power transfer to the vehicle's wireless power receiver as it moves [45].
- Vehicle to Grid (V2G): This refers to a system in which electric vehicles can be used to provide supplemental power to the electrical grid. With this technology, electric vehicles not only draw energy from the grid (often causing issues like voltage sags in the area or overloading the grid) but can also feed energy back into the grid to contribute to its stabilization. In a V2G system, the electric vehicle connects

to the grid through a charging station, which is primarily connected to substation equipment (medium voltage). In cases where the grid needs additional power, energy can be drawn from the electric vehicle's battery through the charging station and supplied to the grid. Conversely, when the grid has surplus power, the charging station can effectively charge the electric vehicle's battery and allow it to store energy for later use [46].

Vehicle Battery Type – Technology: In terms of vehicle battery type technologies, the categorization is as follows:

- Lead-Acid Batteries: Lead-acid batteries are one of the types of batteries commonly used in modern electric vehicles. They are known for being a relatively inexpensive energy storage technology due to the low cost of the raw materials. However, they have certain disadvantages, such as a limited lifespan. The advantages of lead-acid batteries include their low material costs, high safety levels, and recyclability. They are also known for their high recycling rates. However, due to their low energy density and limited energy storage capacity, these batteries are typically used in vehicles designed for shorter distances and lower weights, such as electric scooters. Lead-acid batteries are not commonly found in long-range electric vehicles, where higher-capacity and longer-lasting battery technologies like lithium-ion batteries are preferred for their ability to provide more energy and longer driving ranges [47].
- Nickel-Cadmium (NiCd) Batteries: Nickel-cadmium (NiCd) batteries are another type of battery technology. These batteries offer higher energy storage capacity compared to lead-acid batteries but come with a significantly higher cost. However, they are not recommended for use in electric vehicles due to their environmental impact, primarily related to the cadmium content, as well as the high cost of the batteries. Cadmium is a toxic heavy metal, and its use in batteries raises environmental concerns, especially in terms of disposal and recycling. As a result, NiCd batteries have been largely phased out in favor of more environmentally friendly and cost-effective battery technologies like lithium-ion batteries for most applications, including electric vehicles.Lithium-ion batteries have become the dominant choice for electric vehicles due to their higher energy density, longer lifespan, and lower environmental impact compared to older battery technologies like NiCd [47].
- Nickel-Metal Hydride (NiMH) Batteries: Nickel-metal hydride (NiMH) batteries are a more recent iteration of nickel-cadmium (NiCd) batteries. They do not contain toxic cadmium as the primary material but offer similar efficiency. In contrast to their earlier version, NiMH batteries can achieve nearly double the energy density and have a longer lifespan. However, due to the high cost of the raw materials used in NiMH batteries, they cannot compete with lithium-ion batteries in terms of cost-effectiveness. As a result, lithium-ion batteries have largely surpassed NiMH batteries in popularity, especially in applications like electric vehicles. While NiMH batteries are more environmentally friendly than NiCd batteries due to the absence of cadmium, they still face limitations in terms of energy density and cost competitiveness compared to lithium-ion batteries [47].

- Lithium-Ion (Li-ion) Batteries: The term ”Lithium-Ion batteries” refers to a variety of material combinations used to create a battery, such as lithium cobalt oxide (Li-Co Oxide), lithium manganese oxide (Li-Mn Oxide), lithium iron phosphate (Li-Fe Phosphate), and lithium nickel cobalt manganese oxide (Li-Ni-Mn-Co Oxide). The characteristics of Li-ion batteries, such as power, lifespan, performance, and safety, largely depend on the specific material combinations used in their construction. However, it is well-known that this technology achieves the highest energy and power density, resulting in low weight and volume [47].

Li-ion batteries are considered the most capable and reliable batteries because they can store up to three times more energy (per unit of weight and volume) compared to conventional lead-acid and nickel-metal hybrid batteries. Due to their characteristics and high energy storage capacity, they find widespread applications in sectors like aviation and electric vehicles. Li-ion batteries have become a dominant choice for portable electronic devices, electric vehicles, and various other applications due to their high energy density, lightweight design, and long cycle life [33, 47].

Installation Area Network (Thermal Limits and Power): During the design and selection of the optimal location for the installation of electric vehicle battery charging infrastructure, the interconnection network of the area with the charging station is taken into consideration. More specifically, many studies related to the development of EV (Electric Vehicles) usage focus on assessing the impacts of charging on the electrical grid. These impacts may include effects on transformer operation [48], power system quality [49], grid voltage instability [21], adequate electrical energy generation [50], and possible power losses [51]. Therefore, according to the studies and sources, the limitations that need to be studied and evaluated before the installation of electric vehicle charging infrastructure are as follows:

- Power Infrastructure: Charging station installations require substantial additional power capacity to charge multiple vehicles simultaneously. This can sometimes lead to issues on the grid, especially when the power infrastructure is not sufficient to support the increased or sudden demand [29]
- Distribution Point Overload: In areas with a high concentration of electric vehicles, charging can overload distribution points, particularly when the infrastructure hasn’t been adapted for the increased power demand.
- Load Management: Load management is crucial to avoid extreme charging peaks and address any imbalances in the grid [29]
- Distance from Substation: The distance from the nearest electrical substation can affect power availability for charging [29]

These limitations can be addressed through investments in urban power infrastructure, intelligent load management, the development of advanced grid systems, and the integration of alternative energy sources, such as Renewable Energy Sources (RES), to supply the electric vehicle charging stations.

Installation Cost: The total costs considered during the design of a charging station are divided into installation costs, operational costs, and maintenance costs. These costs should align with the available budget. Specifically, according to Liu and

Bie [52], when estimating the cost of a charging station, whether it's for direct current (DC) or alternating current (AC) installation, various factors must be taken into account, such as the cost of installing the charging infrastructure, land costs, network costs, and delay costs. However, it's challenging to determine these costs with precision, as they depend on factors like the manufacturer, the type of charger, the local infrastructure, the area and land use, as well as the demand.

To sum up, the basic parameters for making a decision regarding the placement of an electric vehicle charging station in the urban network, which could serve freight routes and deliveries, are as follows:

- Approach to congested traffic areas: Charging stations are typically more sought after when located in high congestion areas and central arteries, such as highways and main roads. This contributes to easy access to charging and the convenience of drivers in terms of their vehicle's autonomy, as well as the uninterrupted flow of their deliveries. Availability of parking spaces: The installation of charging stations is recommended areas with sufficient parking space availability [18]. Specifically, electric vehicle drivers need a parking space during the charging process. Therefore, during the planning stage, it is necessary to consider that the number of parking spaces should be proportional to the number of charging stations for the specific location under study.
- Access to amenities: It is beneficial to install charging stations in areas near shopping centers, restaurants, or entertainment venues. This allows drivers to engage in other activities or even perform some form of distribution during their vehicle's charging. (This depends on the type of charging; in the case of wireless charging, the distributor may distribute their goods while charging their vehicle) [53].
- Access to electrical infrastructure: Charging stations require a stable and robust power supply. Therefore, access to electrical infrastructure, such as substations or transmission lines, is crucial to ensure the reliability and effectiveness of charging operations and the network as a whole [29].
- Collaboration with the power company: It is essential for a given area to assess the network's capacity to ensure that the power station's power requirements can be met without overloading the network. Additionally, it needs to be ensured that there are no connectivity issues. Therefore, areas with high capacity, high voltage (network resilience), and access to renewable energy sources are recommended. In the case of energy extraction from renewable sources, the planning and installation process becomes more straightforward, as it does not impose a significant burden on the network.

2.2 Mathematical Models

The problem examined in this thesis is based on the classic Facility Location Problem (FLP). Hakimi [54] proposed the concept of the p-center location model and p-median location model in 1964. The set-coverage location model (SCLM) was proposed by Toregas et al. [55], while few years later Church and ReVelle [56] proposed the maximum coverage location model (MCLM). These location selection problems are applied to network facilities location selection, such as factory, warehouse, station, etc. However, past studies has shown that some location problems cannot be solved by existing models [57, 58].

The objective of the FLP is to optimally select one or more locations from a large set of candidate locations while incorporating constraints on the selected locations. In the field of electric vehicles, studying the FLP can help determining suitable locations for the installation of public charging stations and the number of chargers in each area or point [53]. Initially, a literature review is conducted to investigate the FLP in the context of finding the optimal location for electric vehicle charging stations. Subsequently, the combined problem of Facility Location and Vehicle Routing is reviewed.

The need for recharging electric vehicle batteries can significantly impact the accessibility of an area with high rates of electric vehicle deliveries or freight distribution. For this reason, it is necessary to design and select the optimal location (geographic points) for charging station infrastructure to maximize the autonomy of battery-powered vehicles, taking into account the spatial distribution of the network [28]. This is typically achieved by developing new models that extend the Charging Station Location Problem (CSLP) formulation [59].

Zhu et al. [60] focused on finding the optimal locations for charging stations and determining the charging infrastructure to be installed at each available point. Initially, they developed a linear programming model with the goal of minimizing the total cost of the charging station installations. However, in this initial model, the available locations for potential charging stations were point-based. In a subsequent version of their model, they modified the available locations. Instead of point-based locations, they used line segments defined by two nodes. Both versions of the model were solved using a genetic algorithm, and it was observed that the higher cost reduction was achieved in the second case. This was attributed to the consideration that a significant factor in determining the optimal location is the distance that a driver can travel to recharge his/her vehicle. The availability of different types of locations (points and line segments) allowed for a more flexible approach in optimizing the placement of charging stations while considering the travel distance of drivers.

Kong et al. [13] developed a method which takes into account many factors that affect the selection of charging station locations on the road network. They developed a multi-layered model that simultaneously optimizes both cost-related factors of charging stations (installation cost, land cost, traffic congestion impact, and station distribution within a given area) in the first layer and the operation of the charging station and its impact on vehicle drivers, traffic flow, and network safety in the second layer. The solution was implemented using a simulation platform in Beijing, China, based on dynamic real-time data. The results demonstrated that the proposed model contributes to cost optimization, allowing for the identification of optimal locations for charging station installations. Yazdekhasti et al. [53] aimed to maximize the level of service, cover the demand and minimize the cost of installing charging infrastructure. They developed a multi-level model focusing on three stages. In the third stage of the model, they determined the locations of charging stations, the distribution, and the number of charging slots. Initially, they defined an acceptable distance between available charging station installation points, calculated the acceptable radius where candidate station points would be placed to maximize service levels and cover the demand. Finally, they calculated the battery capacity and the available power of vehicles that would require recharging. When applying their model to California, the results showed the following: when there is a low number of available charging stations in the network, increasing battery capacity requires the installation of charging stations to a central area of the network. Conversely, when there is a significant number of available charging stations in the network, increasing the basic battery capacity causes the station locations to shift towards the periphery. Additionally, by selecting a city with low congestion rates near a larger urban center, demand in these areas and neighboring ones can be optimally covered by minimized costs.

Ahangar et al. [61] developed a two-level model (bi-objective mathematical model) with the aim of determining the optimal locations for installing charging stations. In the first level, the goal was to minimize costs, while the second level focused on maximizing drivers' satisfaction. To solve the model, it was assumed that two types of charging technologies are available, while the acceptable distance that drivers are willing to travel to charge their vehicles is taken into account. The numerical results indicated that the available budget for building charging stations must be increased in order to reduce the number of users who travel a greater distance than desired to charge their vehicles.

The authors [62] proposed a multi objective optimization problem taking into consideration transportation energy loss cost, station build-up cost and sub-station energy loss cost for finding the optimal location of Fast Charging Stations, which was solved by the binary lighting search algorithm . Sadeghi-Barzani et al.[63] formulated a mixed integer nonlinear problem (MINLP) by considering the CS equipment cost, land costs electrification cost, electric grid loss cost, and EV loss cost ,while the optimal solution is obtained with GA. The authors [64] have analyzed the finding of the optimal location of parking lots by maximizing the revenue of parking lots and have considered the energy costs such as power loss costs, reliability cost, voltage improvement cost, and parking lot cost, whereas the solution of the model is obtained with the usage of GA. He et al. [65], taking into account the costs associated with batteries, charging stations, and energy storage systems, formulated a mixed-integer linear programming. This model aims to determine the strategic deployment of charging stations and the configuration of batteries and energy storage systems in an optimal manner. Based on cost model and genetic algorithm Zhou et al. [66] constructed a total social cost model covering economic and environmental costs, in order to minimize the construction costs of charging station. As for economic costs, they include construction costs and operating costs, while the environmental costs include the cost of carbon dioxide emissions. They took into consideration constraints such as charging supply and charging distance. A sensitivity analysis is conducted, in order to observe the possible relevant factors. The findings indicate that the placement of charging stations is highly influenced by factors such as the quantity of charging stations, the demand for charging at intersections, and the probability of daily charging. Furthermore, the overall social cost is directly associated with both the number of charging stations and the probability of charging.

Viewed from a different perspective, and not with the primary goal of minimizing the total cost, Ma and Xie [67] studied the problem of determining the locations of charging stations focusing on minimizing the total time of delays and the waiting time in line for charging during the day. Their modeling method was a bi-level optimization problem, employing mixed-integer linear programming, while the Lagrangian method was chosen as the solving method. The study was applied to Luxembourg for fast charging and continuous current infrastructure. The results of the model showed that the optimal charging station locations can be determined given externally defined parameters such as demand, vehicle battery size, and the number of chargers that would be deployed. Moreover, a mixed-integer programming model has been developed by [68] in order to maximize the overall plug-in EVs flows in the network and the GA has used to solve the proposed problem. [69] proposes a model based on parameters such as power loss, voltage deviation and EVs charging costs infrastructure in order to find the optimal location of charging station and and the optimal implementation of renewable energy sources which is solved by differential evolution algorithm. Recently, in study of [70] the location problem has received considerable attention, with a focus on analyzing both supply and demand aspects, incorporating the psychological factors of drivers. Luo et al. [71] and Balakrishna et al.[72] have not only proposed the deployment of charging stations (CS) but also recommended the integration of distributed generation sources. Their studies have demonstrated that integrating distributed generation can alleviate unforeseen loads on established urban distribution power grids, which have typically served cities for many years. A holistic approach was taken by Bouguerra et al.[73], which considered factors such as driving range, real-world constraints, investment expenses, and user convenience. A weighted model was developed to ascertain the optimal location and capacity of the charging station, taking into account all these elements. In this research [74], an innovative station-level optimization framework has been introduced to execute the most efficient charging station pricing policy and charging schedule. This model seamlessly integrates human behavior, providing a clear and effective representation of drivers' decision-making processes when it comes to charging their vehicles.

An approach based on partitioning has been introduced by [75] to find optimal station location by minimizing traffic loss. Furthermore, Frade et al.[76] has identified the ideal locations for stations in Lisbon with the aim of optimizing accessibility for electric vehicle (EV) owners. Optimal station location was examinated [77] to minimize station infrastructure's and operating cost. An analytical method has been proposed in Hanabusa' study [78] to find optimal station location considering driving patterns. Graph theory has been used in [79] to find optimal size and location of charging stations. A two step technique was proposed in [80] to determine optimal location and size of the charging stations. Particle swarm optimizazation technique was used in [80] for optimal charging station planning. In this research, Wang et aL. [81] a traffic-constrained optimization framework was introduced to ascertain the most efficient planning of electric vehicle charging stations.

Schiffer et al. [82] focused on the study and solution of the Electric location routing problem with time windows and partial recharges (ELRPTWPR). Specifically, they found that electric vehicle charging stations can be located near customer locations, and the time during distribution and loading can be used for vehicle charging. This research demonstrated the importance of combining the location of charging stations and the routes of electric vehicles, particularly when the final destination of the distribution is not far from warehouses or the vehicle's starting location. Subsequently, Schiffer and Walther [83] studied and compared the ELRPTWPR and E-VRPTWPR (Electric vehicle routing problem with time windows with partial recharging). They found that the ELRPTWPR provided optimal solutions in all cases. According to their research, electric vehicles can charge while serving (distributing and loading goods), reducing the delay times to and from charging stations during off-peak hours. Lastly, Sun et al. [58] examined the location problem by developing an optimal model for electric charging station placement. However, they did not consider routing based on residents' travel demand in the studied area. Their findings indicated that for short distances, drivers would use slow chargers for charging, while for long distances, fast charging facilities would be utilized. Charging station locations were determined based on maximizing the level of service, and an economic budget constraint was imposed to determine each location. Tang et al. [84]also focused in The optimal location of energy supply centers for EVs. Considering the routing problem and EV autonomy they developed a decision problem, which determines the optimal number of CS, locations, allocation of users to each CS, and economic dispatching policy. Kinay et al.[85] developed an innovative comprehensive modeling framework for the planning of refueling station infrastructure. The model specifically concentrated on the strategic placement of fast-charging stations for long-range battery electric vehicles. It introduced a new approach to addressing the facility location problem related to the installation of refueling and recharging infrastructure for vehicles[86].

In Table 1 the most typically considered aspects in mathematical models that select the locations of charging stations are presented.

In addition, Table 2 provides a summary of the objectives, mathematical formulations, solution methods, and applications of past studies.

As we can see, numerous pieces of literature have dedicated significant attention to the optimal arrangement of charging stations. This underscores the wide-ranging interest in charging station research. Previous investigations have primarily centered on a variety of factors influencing charging station layouts, the development of optimal charging station models, and the introduction of diverse model-solving techniques. These studies have made substantial contributions within these domains and serve as a foundational basis for future research. Concurrently, the majority of existing literature delves into aspects such as charging station technology, user preferences and behaviors, environmental advantages, and thereby showcases the diverse range of optimization methods employed [66].

From the studies presented in Tables 1 and 2, the closest prior art to this work is the study of Zhu et al. [60]. The study of Zhu et al. [60] is a variation of the FLP. The approach developed in this work differs from the work of [60] in the following aspects:

1. it focuses on freight transport considering heterogeneous fleets of electric vehicles, such as electric light trucks and electric medium trucks;
2. it does not consider the installation costs as part of the objective function, but as model constraints;

Table 1 Considered aspects in selected past studies

Study	**Type of charger**		**Infrastructure**		**Drivers**	**Time**	**Costs**		**Tech. characteristics**		**Demand**	**Energy**
	Regular	Fast	Number CS/chargers	Distance Tolerance	Behavior	Delays	Install	Operate	Traffic flow	Battery capacity	Charging demand	Power grid
Zhu et al. [60]			✓	✓			✓	✓				
Kong et al. [13]		✓			✓	✓	✓		✓		✓	✓
Ma and Xie [67]		✓				✓					✓	
Yazdekhasti et al. [53]							✓	✓	✓		✓	
Guo and Zhao [11]		✓					✓	✓				
Ahangar et al. [61]	✓	✓	✓	✓	✓		✓					
Schiffer and Walther [83]			✓	✓			✓	✓		✓		
Sun et al. [58]	✓	✓	✓	✓	✓	✓	✓				✓	

Table 2 Summary table of mathematical models from past studies

Study	Objective Function	Mathematical Formulation	Solution Method	Application
Zhu et al. [60]	Optimize the location of charging infrastructure and the number of chargers that should be installed in each charging station, to minimize the total cost.	single weighted objective	genetic algorithm-based method	Beijing, China
Kong et al. [13]	minimize the total construction cost of all charging stations and optimization of operators, drivers, vehicles, traffic condition and power grid	bi-level optimization-simulation model	real-time data analysis	Simulation in Beijing, China
Ma and Xie [67]	minimize the total travel time and queuing delays for daily charging operation	MILP (Mixed integer linear program)	Lagrangian Relaxation (LR) method-Heuristic	Luxembourg
Yazdekhasti et al. [53]	minimize the portion of the demand uncovered by the charging stations, and objective to minimize the charging station installation cost	bi-level optimization-simulation model / MILP	Metaheuristic Method/ Hybrid Multi Objective Scatter Search Variable	Artificial network using data from California
Ahangar et al. [61]	minimizes the difference between system revenues and costs in which revenues are generated from charging electric vehicles, and costs are incurred by constructing charging stations and installing chargers and to minimize the amount of customer dissatisfaction	bi-objective mixed-integer linear mathematical model	Lagrangian Relaxation (LR) method	Tehran, Iran
Schiffer and Walther [83]	Minimization of total distance,number of vehicles and CSs used, total costs: investments and operations costs	bi-objective mixed-integer mathematical model	genetic algorithm-based method	Simulation
Sun et al. [58]	maximize the coverage of all EV flows, which intends to locate fast recharging stations on paths and slow charging stations on nodes	mixed integer programming	CPLEX	Simulation with data from China

3. it adds new aspects in the model formulation, such as the capacity of the charging station and the capacity of the battery of the vehicles.

3 Methodology

Optimization methods find application across various domains, aiming to maximize or minimize specific objective functions of interest. These objectives can encompass minimizing production costs, maximizing profits, reducing raw material usage in product development, or optimizing production efficiency [87], to name few. Some the optimization problem formulations that widely appear in practice are:

Linear Programming (LP): LP is used to optimize a linear objective function subject to linear equality and inequality constraints [88].

Integer Linear Programming (ILP): Similar to linear programming, but with the additional constraint that all decision variables must take integer values. ILP is applied in situations where variables represent whole quantities, like in production planning [89].

Nonlinear Programming (NLP): NLP deals with optimization problems where the objective function or some constraints are nonlinear. It is used in various fields, including engineering design and financial modeling [88].

Quadratic Programming (QP): QP is a special case of nonlinear programming where the objective function is quadratic, and constraints are linear. It is used in portfolio optimization, robotics, and structural optimization [90].

Mixed-Integer Linear Programming (MILP): MILP combines elements of linear and integer programming to handle problems with both continuous and discrete decision variables. It is used in network design, scheduling, and logistics [91].

Dynamic Programming: This method is suitable for solving optimization problems with a sequential decision-making process. It is widely used in control theory, finance, and operations research [92].

In this thesis, the model of Zhu et al. [60] is extended, which is a variation of the classic FLP, in order to specify the optimal locations of charging stations for electric trucks in a fixed study region. In their study, Zhu et al. [60] focused on minimizing the total charging stations construction costs and attaining a desired traveler convenience by minimizing the distance that travelers are willing to going through.

In our model formulation the main idea is similar to [60], but there are some key differences. First of all, focus is given on the freight transport instead of passenger transport. Second, an heterogeneous fleet of electric vehicles is considered, such as electric light trucks and electric medium trucks. Third, the parameter of the cost is not included in the objective function. On the contrary, the cost aspect is considered as an additional problem constraint, given that the budget of constructing charging stations is limited. Finally, new parameters such as the capacity of the charging stations and the capacity of the battery of the vehicles are included in the model formulation.

To formulate the problem, the sets, parameters and decision variables are defined. These are presented in Table 3.

Table 3 Nomenclature

Sets	
R	Set of available electric vehicles (EVs).
I	Set of the EVs destination locations, from which they would need to travel to a charging station for recharging.
K	Set of vehicle types (light and medium trucks).
J	Set of all possible charging station locations.
Parameters	
P_r	the destination location $i \in I$ that is matched with each EV $r \in R$
Q	capacity of charging station.
Q_k	battery capacity of vehicle of type $k \in K$.
D_r	tolerance distance, indicating the maximum distance each EV $r \in R$ is willing to cover for charging.
c_j	installation cost of charger, depending on its location $j \in J$.
B	available budget for installing charging stations, including infrastructure, energy, and maintenance.
$m_{r,k}$	0-1 parameter, where $m_{r,k} = 1$ if vehicle r is of type k and 0 otherwise.
d_{ij}	Distance from point i to charging station location j
Decision Variables	
n_j	Number of chargers that will be installed in charging station location j
x_j	A binary variable that is 1 if a charging station will be installed in region j, and 0 otherwise
y_{rj}	A binary variable that is 1 if vehicle $r \in R$ that needs to recharge after arriving at destination location P_r chooses to charge in a charging station in region j, and 0 otherwise

In our model, the goal is to minimize the distance that the truck drivers are going to cover in order to charge their vehicles. In this way, focus is given on minimizing the empty kilometers traveled for vehicle charging purposes. The mathematical formulation is based on the following assumptions:

1. Each charging point can accommodate as many vehicles as its energy power (supply) allows it to do so.
2. Aiming at the strategic planning level, vehicles that charge at the same charging point can pre-schedule their chargings at different times of the day to avoid queuing delays, and thus delays due to queuing at the charging points are not considered as an extra cost (see [60]).
3. Truck drivers need to charge their vehicle when they arrive at a particular point i at which they have finished their deliveries and their state of charge (SoC) does not allow them to perform a new round of pickups and deliveries without charging.

Usually, the charging points are far away from the points $i \in I$ where the truck drivers need to charge. Due to this fact, drivers would have to take a detour and travel from point i to a charging station. This detour is translated into a travel cost that needs to be minimized by placing the charging stations at strategic locations. In practice, each truck trip is matched with one location i from which it will need to travel to a charging station. It is also matched with one type of Plug-in Electric Vehicles (PEVs) (light or medium truck). While we seek to minimize the travel distance of trucks to the charging station, an upper bound (threshold) is also imposed to the maximum distance a PEV is willing to travel for charging purposes to avoid excessive empty kilometers traveled for particular vehicles.

The mathematical formulation of the problem is provided below.

$$\min \sum_{j\in J}\sum_{r\in R} d_{P_r,j} y_{r,j} \tag{1}$$

$$\text{subject to:} \quad \sum_{j\in J} y_{r,j} = 1 \qquad \forall r \in R \tag{2}$$

$$x_j \geq y_{r,j} \qquad \forall r \in R, j \in J \tag{3}$$

$$x_j \leq n_j \qquad \forall j \in J \tag{4}$$

$$n_j = \sum_{r\in R} y_{r,j} \qquad \forall j \in J \tag{5}$$

$$d_{P_r,j} y_{r,j} \leq D_r \qquad \forall r \in R, j \in J \tag{6}$$

$$\sum_{j\in J} c_j n_j \leq B \tag{7}$$

$$\sum_{r\in R}\sum_{k\in K} y_{r,j} m_{r,k} Q_k \leq Q \qquad \forall j \in J \tag{8}$$

$$n_j \in \mathbb{Z}_+ \qquad \forall j \in J \tag{9}$$

$$x_j \in \{0,1\} \qquad \forall j \in J \tag{10}$$

$$y_{rj} \in \{0,1\} \qquad \forall r \in R, j \in J \tag{11}$$

The objective function (1) minimizes the total distance that drivers need to cover in order to charge their vehicles. Constraints (2) ensure that each vehicle $r \in R$ is charged in exactly one region $j \in J$. Constraints (3) denote that the EVs can be charged in region j only when there is charging station located in region j. Constraints (4) ensure that a charging station is located only when there are vehicles needing to be charged at this station. Constraints (5) denote that the number of the chargers in region j is equal with the number of EVs that choose to be charged in region j. This condition ensures that there are enough chargers in each charging station to serve all the drivers without delays. Constraints (6) ensure that each EV $r \in R$ which finishes its trip at location P_r chooses to be charged in region j only when the distance between P_r and j is not larger than D_r. Constraints (7) denote that the total cost of installation for all the chargers is no greater than the given budget. Constraints (8) ensure that the capacity of stations in energy power is sufficient to cover the demand. The remaining constraints ensure that decision variables n_j take non-negative integer values and x_j, y_{rj} binary values.

The resulting mathematical program is an Integer Linear Program (ILP) that can be solved to global optimality with Branch-and-Cut and a solution method for linear programming (i.e., Simplex or Karmarkar's Interior Point Method).

4 Numerical Experiments

In this section, a description of the data utilized for the computational experiments is provided. Next, the performance of the proposed model for problem instances of practical scale is discussed. In addition, the impact of the tolerance distance and total budget in the location decisions is demonstrated. All numerical experiments are coded in Python 3.11 (64-bit) on a desktop computer equipped with an Intel(R) Core(TM) i7-1065G7 processor 1.50 GHz and a 8,00 GB RAM. The optimization solver used is the GUROBI 10.02 optimizer.

4.1 Toy Network

For demonstration purposes, an application of the proposed mathematical model in a toy network is presented. The toy network is presented in Fig.2. It involves 10 truck locations represented by a black square, and 4 potential charging station locations represented by a triangle (in gray colour). We consider that there are 50 EVs destined to one of the predefined locations. Each EV is either a medium or a light vehicle, with battery capacity equal to 70 and 250 kWh, respectively. The station capacity for each of the potential charging stations is equal to 3400 kWh.

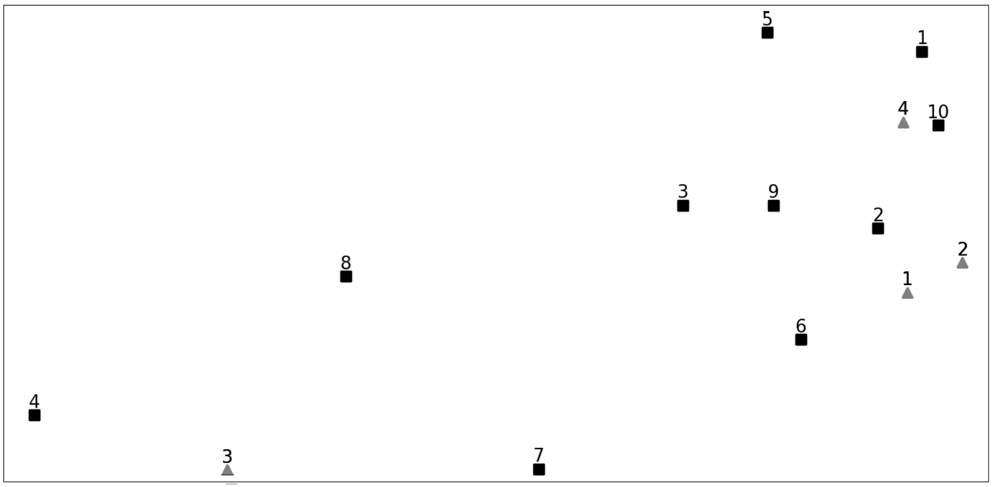

Fig. 2 Toy network with 10 locations (in squares) and 4 potential charging station locations (in triangles)

Since the toy network used in this demonstration is small, it can be solved to global optimality. The number of EVs assigned to charging stations and the total travel cost are presented in Table 4. The optimal solution demonstrates that location 2 is not selected as a charging station location. Thus, there are 10, 17 and 23 truck trips served by locations 1, 3 and 4, respectively.

The analytic solution indicating the assignment of EVs to charging stations is presented in Table 5.

Table 4 Optimal solution of the toy network

station	number of EVs
1	10
2	0
3	17
4	23
total travel cost:	1487.69

4.2 Computational results

For the initial assessment of the proposed model, 20 problem instances have been initially generated. The generated problem instances involve 100, 400 and 1000 locations (as a total of truck locations and potential charging stations locations). Five network schemes are considered, involving different locations, charging station locations and trucks destined to the network locations. The number of locations (I), the number of potential charging stations (J) and the number of trucks-drivers (D) involved in each scenario, are demonstrated in Table 6. For each scenario, five problem instances were generated (a,b,c,d,e), based on the well-known data set of [93], originally introduced for the Vehicle Routing Problem with Cross-Docking (VRPCD). An heterogeneous fleet of EVs is considered with two vehicle types: light and medium trucks. Each vehicle type is associated with a different level of battery usage. Finally, for all problem instances a common value for the tolerance distance value (D_r) for each driver, is considered.

Table 7 presents the computational results obtained by the proposed model. Table 7 reports the results of the cost objective function. Each row of Table 1 provides the best solutions (bst) obtained, the %gap and the time (t) in seconds, required to obtain bst, over each problem instance.

Specifically, the results indicate that, with a budget of 4,000,000 and a tolerance distance of 60 in cases with 70 locations and 30 potential charging station locations(L_70 S_30 scenario), the same number of stations that are selected is on average the same, while there is an increase in the average number of charger slots encountered per charging station. The same observation applies to the next two instances. It is worth noting that for the larger scale problem instances, the time required to find the optimal solution also increases.

4.3 Sensitivity Analysis

In order to assess the important model parameters, further computational experiments were conducted considering different values for the capacities of the charging stations (Q), the available budget for installing charging stations (B) and the tolerance distance (D_r). More specifically, three levels (Low, Medium and High) at each of the three model parameters under examination are considered. The values of each parameter at each level, are indicated in Table 8.

Table 5 Optimal assignment of EVs to charging stations

EV	location	station
1	5	4
2	4	3
3	2	1
4	4	3
5	10	4
6	8	3
7	6	1
8	8	3
9	10	4
10	1	4
11	2	1
12	4	3
13	1	4
14	3	4
15	5	4
16	2	1
17	3	4
18	3	4
19	8	3
20	6	1
21	2	1
22	10	4
23	4	3
24	8	3
25	2	1
26	1	4
27	7	3
28	4	3
29	2	1
30	9	4
31	5	4
32	5	4
33	8	3
34	7	3
35	2	1
36	7	3
37	9	4
38	5	4
39	9	4
40	9	4
41	7	3
42	4	3
43	2	1
44	10	4
45	3	4
46	1	4
47	4	3
48	8	3
49	1	4
50	1	4

EV: ID of EV; location: ID of the location at which is EV is destined; station: ID of the selectedcharging station

Table 6 Scenarios

I	J	D
70	30	100
70	30	400
150	50	400
150	50	1000

I: Number of EVs destination locations; J: Number of possible charging stations; D: Number of EVs destined to all locations

Table 7 Computational results for the generated problem instances

Scenario	bst	gap%	t (sec)
$L\_70\_S\_30\_D\_100$			
a	741.22	0.00%	0.93s
b	1190.22	0.00%	0.58s
c	1027.08	0.00%	0.19s
d	833.44	0.00%	0.18s
e	1122.66	0.00%	0.83s
L_70_S_30_D_400			
a	2306.61	0.00%	1.78s
b	4059.78	0.00%	0.46s
c	3599.00	0.00%	0.33s
d	3042.60	0.00%	0.23s
e	3903.19	0.00%	0.44s
L_150_S_50_D_400			
a	2119.13	0.00%	0.97s
b	2826.01	0.00%	1.82s
c	2307.28	0.00%	0.80s
d	2519.34	0.00%	1.27s
e	2687.52	0.00%	1.51s
L_150_S_50_D_1000			
a	5671.44	0.00%	1,95s
b	6339.16	0.00%	1.97s
c	5190.98	0.00%	1.02s
d	5430.32	0.00%	2.64s
e	5430.32	0.00%	1.81s

An attempt was made to find the smallest threshold values for each parameter, where each scenario can be solved (feasibility). The maximum value used for the parameters in the sensitivity analysis was chosen since tests showed that beyond this threshold, there is no significant differentiation of scenarios in the best objective solution.

Table 8 Parameter values

Scenario	D_r	B	Q
L_70_S_30_D_100			
	48	400.000	550
	60	4.000.000	600
	200	6.000.000	800
L_70_S_30_D_400			
	48	2.000.000	2.000
	60	4.000.000	3.000
	200	6.000.000	4.000
L_150_S_50_D_400			
	48	2.000.000	1.200
	60	4.000.000	1.500
	200	6.000.000	3.000
L_150_S_50_D_1000			
	48	4.000.000	3.000
	60	6.000.000	6.000
	200	10.000.000	9.000

L: Low level; M: Medium level; H: High level

Table 9 demonstrates the computational results for the different levels of each model parameter under examination. In particular, Table 9 displays the computational results considering different levels of the station capacity, Table 11 displays the computational results considering different levels of the available budget and Table 12 displays the computational results considering different levels of the tolerance distance.

We observe that by modifying the capacity of the charging stations, the value of the best objective solution, which is the travel cost, decreases as the capacity increases. However, there is a decrease in the number of stations that are ultimately selected (S^{open}) and an increase in the average number of chargers per station (C^{avg}). This result is logical because with the increase of the capacity of the station, given the battery capacity of electric vehicles, it might be more economically favorable to add additional chargers to an existing station, rather than opening a new one. The results are more apparent for the larger scale problem instances.

Table 10 demonstrates the % difference in the total traveled costs and the number of selected stations, between any two station capacity levels. In particular, the decrease in the solution costs for a network with 70 locations is on average 14.53% and 24.99%, when increasing the station capacity from low to high levels (presented in the fourth column). For a network with 150 locations, the decrease is on average 25.96% and 22.36%. The same conclusions can be drawn for the number of selected stations, where we observe a 12.43% and 18.83% decrease, for the smaller and larger scale problem instances, respectively, when the station capacity increases. Therefore, it is evident that capacity is a parameter that significantly contributes to determining the optimal solution.

Table 9 Sensitivity analysis w.r.t the station's capacity (Q)

Scenario	Q^L			Q^M			Q^H		
L_70_S_30_D_100	bst	S^{open}	C^{avg}	bst	S^{open}	C^{avg}	bst	S^{open}	C^{avg}
a	785.61	27.00	3.70	741.22	26.00	3.85	708.51	26.00	3.85
b	1253.31	30.00	3.33	1190.22	28.00	3.57	1066.01	28.00	3.85
c	1077.06	30.00	3.33	1027.08	28.00	3.57	936.47	27.00	3.70
d	837.07	29.00	3.45	833.44	29.00	3.45	784.45	28.00	3.57
e	1209.24	28.00	3.57	1122.66	28.00	3.57	978.73	26.00	3.85
L_70_S_30_D_400									
a	3377.43	27.00	14.81	2306.61	25.00	16.00	2238.49	24.00	16.67
b	4517.41	29.00	13.79	4059.78	27.00	14.81	3922.12	25.00	16.00
c	4381.77	29.00	13.79	3599.00	27.00	14.81	3436.06	25.00	16.00
d	3472.39	29.00	13.79	3042.60	28.00	14.29	2947.36	28.00	14.29
e	4848.80	30.00	13.33	3903.19	26.00	15.38	3709.81	24.00	16.67
L_150_S_50_D_400									
a	2266.21	47.00	8.51	2119.13	44.00	9.09	2005.31	43.00	9.30
b	3298.55	50.00	8.00	2826.01	44.00	9.09	2574.33	42.00	9.52
c	2546.30	49.00	8.16	2307.28	49.00	8.16	2213.98	45.00	8.89
d	2938.94	50.00	8.00	2519.34	46.00	8.70	2267.87	38.00	10.53
e	3438.07	50.00	8.00	2687.52	45.00	8.89	2362.31	40.00	10.00
L_150_S_50_D_1000									
a	6680.19	48.00	20.83	5671.44	43.00	23.26	5624.30	43.00	23.26
b	7524.99	50.00	20.00	6339.16	44.00	22.73	6282.17	42.00	23.81
c	6617.27	49.00	20.41	5190.98	46.00	21.74	5187.28	45.00	22.22
d	6409.77	49.00	20.41	5430.32	38.00	26.32	5351.78	38.00	26.32
e	7555.11	49.00	20.41	6075.52	41.00	24.39	6001.16	39.00	25.64

Notation: Q^L: Low level of station's capacity; Q^M: Medium level of station's capacity; Q^H: High level of station's capacity; bst: best solution value obtained; S^{open}: Number of stations selected; C^{avg}: Average number of trucks assigned to the stations

Regarding the increase of the total available budget, we observe negligible differences in the number of CS (Charging Stations) that are selected and in the average number of chargers per station. This result, can be attributed to the network characteristics as well as the fact that the strict constraints imposed in our model, do not allow much room for the the exploration of cost-saving opportunities in the solution.

Finally, as part of the sensitivity tests, we attempted to examine the impact of the tolerance distance parameter (D_r) on the optimal solution. The results are presented in Table 12. Note that the empty cells represent an infeasible solution for the particular problem instance. Table 13 demonstrates the % difference in the best solution obtained and the number of selected stations, between any two levels of the tolerance distance.

We can observe that for low levels of the D_r parameter, we do not have an optimal solution for two problem instances. When comparing solutions with increased values of the tolerance distance (60 and 80), we notice differences in some cases, primarily in the best objective and not so much in the number of charging stations that open. It is worth noting that the selected charging stations vary each time as we modify

Table 10 Impact of the station capacity (Q) on the optimal solution

Scenario	bst (%diff)			S^{open}(%diff)		
	Q^M- Q^L	Q^H- Q^M	Q^H- Q^L	Q^M- Q^L	Q^H- Q^M	Q^H- Q^L
L_70_S_30_D_100						
a	-5.65	-4.41	-9.81	-3.70	0.00	-3.70
b	-5.03	-10.44	-17.57	-6.67	-7.14	-13.33
c	-4.64	-8.82	-15.01	-6.67	-3.57	-10.00
d	-0.43	-5.88	-6.71	0.00	-3.45	-3.45
e	-7.16	-12.82	-23.55	0.00	-7.14	-7.14
avg	-4.58	-8.47	-14.53	-3.41	-4.26	-7.53
L_70_S_30_D_400						
a	-31.71	-2.95	-33.72	-7.41	-4.00	-11.11
b	-10.13	-3.39	-15.18	-6.90	-7.41	-13.79
c	-17.86	-4.53	-27.52	-6.90	-7.41	-13.79
d	-12.38	-3.13	-17.81	-3.45	0.00	-3.45
e	-19.50	-4.95	-30.70	-13.33	-7.69	-20.00
avg	-18.32	-3.79	-24.99	-7.60	-5.30	-12.43
L_150_S_50_D_400						
a	-6.49	-5.37	-11.51	-6.38	-2.27	-8.51
b	-14.33	-8.91	-28.13	-12.00	-4.55	-16.00
c	-9.39	-4.04	-15.01	0.00	-8.16	-8.16
d	-14.28	-9.98	-29.59	-8.00	-17.39	-24.00
e	-21.83	-12.10	-45.54	-10.00	-11.11	-20.00
avg	-13.26	-8.08	-25.96	-7.28	-8.70	-15.33
L_150_S_50_D_1000						
a	-17.79	-0.84	-18.77	-11.63	0.00	-11.63
b	-18.71	-0.91	-19.78	-13.64	-4.76	-19.05
c	-27.48	-0.07	-27.57	-6.52	-2.22	-8.89
d	-18.04	-1.47	-19.77	-28.95	0.00	-28.95
e	-24.35	-1.24	-25.89	-19.51	-5.13	-25.64
avg	-21.27	-0.90	-22.36	-16.05	-2.42	-18.83

Notation: Q^L: Low level of station's capacity; Q^M: Medium level of station's capacity; Q^H: High level of station's capacity; bst: best solution value obtained; S^{open}: Number of stations selected; % diff - the % average deviation over two station capacity levels,i.e % diff Q^H - Q^L = 100*((Q^H-Q^L)/Q^L); avg - the average % deviation over all problem instances of each scenario

the parameter values, but their total number remains the same. This is due to the strict constraints we have set, and therefore, by changing the D_r level, we do not see significant differences in the optimal solution. Table 13 indicates small deviations in the total traveled costs and the number of selected stations, when increasing the level of tolerance distance.

Table 11 Sensitivity analysis w.r.t the overall budget (B)

Scenario	B^L			B^M			B^H		
L_70_S_30_D_100	bst	S^{open}	C^{avg}	bst	S^{open}	C^{avg}	bst	S^{open}	C^{avg}
a	741.22	26.00	3.85	741.22	26.00	3.85	741.22	26.00	3.85
b	1190.22	28.00	3.57	1190.22	28.00	3.57	1190.22	28.00	3.57
c	1027.08	28.00	3.57	1027.08	28.00	3.57	1027.08	28.00	3.57
d	833.44	29.00	3.45	833.44	29.00	3.45	833.44	29.00	3.45
e	1122.66	28.00	3.57	1122.66	28.00	3.57	1122.66	28.00	3.57
L_70_S_30_D_400									
a	2306.61	25.00	16.00	2306.61	25.00	16.00	2306.61	25.00	16.00
b	4059.78	27.00	14.81	4059.78	27.00	14.81	4059.78	27.00	14.81
c	3599.00	27.00	14.81	3599.00	27.00	14.81	3599.00	27.00	14.81
d	3042.60	28.00	14.29	3042.60	28.00	14.29	3042.60	28.00	14.29
e	3903.19	26.00	15.38	3903.19	26.00	15.38	3903.19	26.00	15.38
L_150_S_50_D_400									
a	2119.13	44.00	9.09	2119.13	44.00	9.09	2119.13	44.00	9.09
b	2826.01	44.00	9.09	2826.01	44.00	9.09	2826.01	44.00	9.09
c	2307.28	49.00	8.16	2307.28	49.00	8.16	2307.28	49.00	8.16
d	2519.34	46.00	8.70	2519.34	46.00	8.70	2519.34	46.00	8.70
e	2687.52	45.00	8.89	2687.52	45.00	8.89	2687.52	45.00	8.89
L_150_S_50_D_1000									
a	5671.44	43.00	23.26	5671.44	43.00	23.26	5671.44	43.00	23.26
b	6339.16	44.00	22.73	6339.16	44.00	22.73	6339.16	44.00	22.73
c	5190.98	46.00	21.74	5190.98	46.00	21.74	5190.98	46.00	21.74
d	5430.32	38.00	26.32	5430.32	38.00	26.32	5430.32	38.00	26.32
e	6075.52	41.00	24.39	6075.52	41.00	24.39	6075.48	42.00	23.81

Notation: B^L: Low level of budget value; B^M: Medium level of budget value; B^H: High level of budget value; bst: best solution value obtained; S^{open}: Number of stations selected; C^{avg}: Average number of trucks assigned to the stations

5 Conclusions

The need to reduce environmental pollution and limit emissions, which largely originate from the freight transportation sector, has led to the adoption of greener and more sustainable practices. The advancement of technology and the constant effort to introduce new concepts of electric mobility on a large scale have encouraged the scientific community to develop products to reduce the CO2 emissions of conventional private and public transport. Today there are multiple electric mobility alternatives, such as bicycles, cars and generally public and freight transport. However, it has not been possible to massively introduce EVs into the land transportation system due to variables that do not make large scale purchases attractive to potential users in urban and rural areas. These unattractive variables for consumers could be limited autonomy, long charging times, battery life, high costs, and lack of EV charging infrastructure. One of the challenges of electric mobility is the limited battery autonomy of vehicles and, consequently, the restriction on the distance a driver can travel[18]. The lack of charging infrastructure on road networks poses one of the biggest concerns. Therefore,

Table 12 Sensitivity analysis with respect to the tolerance distance (D_r)

Scenario	D_r^L			D_r^M			D_r^H		
L_70_S_30_D_100	bst	S^{open}	C^{avg}	bst	S^{open}	C^{avg}	bst	S^{open}	C^{avg}
a	744.13	27.00	3.70	741.22	26.00	3.85	741.22	26.00	3.85
b				1190.22	28.00	3.57	1190.22	28.00	3.57
c	1049.34	28.00	3.57	1027.08	28.00	3.57	1024.66	28.00	3.57
d	847.88	29.00	3.45	833.44	29.00	3.45	833.44	29.00	3.45
e	1131.58	28.00	3.57	1122.66	28.00	3.57	1122.66	28.00	3.57
L_70_S_30_D_400									
a	2306.61	25.00	16.00	2306.61	25.00	16.00	2306.61	25.00	16.00
b				4059.78	27.00	14.81	4059.78	27.00	14.81
c	3613.45	27.00	14.81	3599.00	27.00	14.81	3599.00	27.00	14.81
d	3097.86	28.00	14.29	3042.60	28.00	14.29	3042.60	28.00	14.29
e	3990.81	26.00	15.38	3903.19	26.00	15.38	3903.19	26.00	15.38
L_150_S_50_D_400									
a	2119.13	44.00	9.09	2119.13	44.00	9.09	2119.13	44.00	9.09
b	2826.01	44.00	9.09	2826.01	44.00	9.09	2826.01	44.00	9.09
c	2307.28	49.00	8.16	2307.28	49.00	8.16	2307.34	49.00	8.16
d	2519.34	46.00	8.70	2519.34	46.00	8.70	2519.35	46.00	8.70
e	2687.52	45.00	8.89	2687.52	45.00	8.89	2687.52	45.00	8.89
L_150_S_50_D_1000									
a	5671.44	43.00	23.26	5671.44	43.00	23.26	5671.44	43.00	23.26
b	6339.00	44.00	22.73	6339.16	44.00	22.73	6339.16	44.00	22.73
c	5190.98	46.00	21.74	5190.98	46.00	21.74	5190.98	46.00	21.74
d	5430.46	38.00	26.32	5430.32	38.00	26.32	5430.46	38.00	26.32
e	6075.52	41.00	24.39	6075.52	41.004	24.39	6075.52	41.00	24.39

Notation: D_r^L: Low level of tolerance distance; D_r^M: Medium level of tolerance distance; D_r^H: High level of tolerance distance; bst: best solution value obtained; S^{open}: Number of stations selected; C^{avg}: Average number of trucks assigned to the stations

it is evident that selecting strategic locations for the installation of charging stations will significantly contribute to increasing the satisfaction of citizens and the service levels.

In this work, the model of [60] is extended, which is a variation of the classic FLP, in order to specify the optimal locations of charging stations for an heterogeneous fleet of electric trucks in a fixed study region. The problem is formulated as an ILP, aiming at minimizing the empty kilometers (travel costs) driven to reach the charging stations, taking into consideration operational constraints such as number of chargers at each station in order to cover the demand for charging, charging station's capacity, battery capacity, total costs, and the distance that a driver is willing to cover in order to charge his/her vehicle.

To validate the proposed model, a toy network was generated and solved by Gurobi Optimizer 10.02. To test the effectiveness of the proposed model on instances of practical scale, a set of problem instances were generated, based on well-known benchmark

Table 13 Impact of the tolerance distance (D_r) on the optimal solution

Scenario	bst (%diff)			S^{open}(%diff)		
	D_r^M - D_r^L	D_r^H - D_r^M	D_r^H - D_r^L	D_r^M - D_r^L	D_r^H - D_r^M	D_r^H - D_r^L
L_70_S_30_D_100						
a	-0.39	0.00	-0.39	-3.70	0.00	-3.70
b	-	0.00	-	-	0.00	-
c	-2.12	-0.24	-2.41	0.00	0.00	0.00
d	-1.70	0.00	-1.73	0.00	0.00	0.00
e	-0.79	0.00	-0.79	0.00	0.00	0.00
avg	-1.25	-0.05	-1.33	-0.93	0.00	-0.93
L_70_S_30_D_400						
a	0.00	0.00	0.00	0.00	0.00	0.00
b	-	0.00	-	-	0.00	-
c	-0.40	0.00	-0.40	0.00	0.00	0.00
d	-1.78	0.00	-1.82	0.00	0.00	0.00
e	-2.20	0.00	-2.24	0.00	0.00	0.00
avg	-1.09	0.00	-1.12	0.00	0.00	0.00
L_150_S_50_D_400						
a	0.00	0.00	0.00	0.00	0.00	0.00
b	0.00	0.00	0.00	0.00	0.00	0.00
c	0.00	0.00	0.00	0.00	0.00	0.00
d	0.00	0.00	0.00	0.00	0.00	0.00
e	0.00	0.00	0.00	0.00	0.00	0.00
avg	0.00	0.00	0.00	0.00	0.00	0.00
L_150_S_50_D_1000						
a	0.00	0.00	0.00	0.00	0.00	0.00
b	0.00	0.00	0.00	0.00	0.00	0.00
c	0.00	0.00	0.00	0.00	0.00	0.00
d	0.00	0.00	0.00	0.00	0.00	0.00
e	0.00	0.00	0.00	0.00	0.00	0.00
avg	0.00	0.00	0.00	0.00	0.00	0.00

Notation: D_r^L: Low level of tolerance distance; D_r^M: Medium level of tolerance distance; D_r^H: High level of tolerance distance; bst: best solution value obtained; S^{open}: Number of stations selected; % diff - the % deviation over two tolerance distance levels,i.e % diff D_r^H - D_r^L = 100*((D_r^H - D_r^L)/D_r^L); avg - the average % deviation over all problem instances of each scenario

datasets in the literature. The results show that the developed model can effectively obtain optimal solutions for realistic problem instances.

Furthermore, this thesis performs sensitivity analysis to assess the impact of various factors on the selection of charging station locations. The impact of model parameters such as the charging station's capacity, the total budget, and the tolerance distance is examined. Results were collected for three values per parameter: low, medium, and high, in order to observe variations in the outcomes. The results indicate that the capacity of the charging station significantly affects the results, as an increase in this parameter leads to a notable reduction in travel costs and a decrease in the number of stations opened. Additionally, in tests involving adjustments to the budget, it was observed that the budget does not significantly affect the total travel costs for all problem instances. This is primarily due to specific network characteristics, such as geographic location, and the stringent constraints imposed, such as distance tolerance and station battery capacity constraints. Conversely, increasing the distance tolerance has a negligible impact on the optimal solution.

Our contribution represents a first step towards research on the strategic planning of electric freight fleets. Future work has to be done on the development of meta-heuristic solution methods capable of solving large-scale instances for real world applications in acceptable computational times. Furthermore, the present work could also be extended by considering additional components such as the vehicle service times and charging times.

References

[1] Agency, E.E.: Greenhouse gas emissions from transport in europe. tech. rep., EEA (2019)

[2] Napoli, G., Polimeni, A., Micari, S., Dispenza, G., Antonucci, V.: Optimal allocation of electric vehicle charging stations in a highway network: Part 2. the italian case study. Journal of Energy Storage **26**, 101015 (2019)

[3] Marsden, T., Banks, J., Bristow, G.: Food supply chain approaches: exploring their role in rural development. Sociologia ruralis **40**(4), 424–438 (2000)

[4] Galati, A., Giacomarra, M., Concialdi, P., Crescimanno, M.: Exploring the feasibility of introducing electric freight vehicles in the short food supply chain: A multi-stakeholder approach. Case Studies on Transport Policy **9**(2), 950–957 (2021)

[5] Sanchez-Sutil, F., Hernández, J., Tobajas, C.: Overview of electrical protection requirements for integration of a smart dc node with bidirectional electric vehicle charging stations into existing ac and dc railway grids. Electric Power Systems Research **122**, 104–118 (2015)

[6] Abid, M., Tabaa, M., Chakir, A., Hachimi, H.: Routing and charging of electric vehicles: Literature review. Energy Reports **8**, 556–578 (2022)

[7] Huang, Y., Wu, X., Jing, J.: Research on the electric vehicle heat pump air conditioning system based on r290 refrigerant. Energy Reports **8**, 447–455 (2022)

[8] Chakir, A., Abid, M., Tabaa, M., Hachimi, H.: Demand-side management strategy in a smart home using electric vehicle and hybrid renewable energy system. Energy Reports **8**, 383–393 (2022)

[9] Lan, H., Hao, D., Hao, W., He, Y.: Development and comparison of the test methods proposed in the chinese test specifications for fuel cell electric vehicles. Energy Reports **8**, 565–579 (2022)

[10] Soares, J., Almeida, J., Gomes, L., Canizes, B., Vale, Z., Neto, E.: Electric vehicles local flexibility strategies for congestion relief on distribution networks. Energy Reports **8**, 62–69 (2022)

[11] Guo, S., Zhao, H.: Optimal site selection of electric vehicle charging station by using fuzzy topsis based on sustainability perspective. Applied Energy **158**, 390–402 (2015)

[12] Alhazmi, Y.A., Mostafa, H.A., Salama, M.M.: Optimal allocation for electric vehicle charging stations using trip success ratio. International Journal of Electrical Power & Energy Systems **91**, 101–116 (2017)

[13] Kong, W., Luo, Y., Feng, G., Li, K., Peng, H.: Optimal location planning method of fast charging station for electric vehicles considering operators, drivers, vehicles, traffic flow and power grid. Energy **186**, 115826 (2019)

[14] Kleiner, F., Brokate, J., Blaser, F., Friedrich, H.E.: Quantitative analysis of the public charging-point evolution: A demand-driven spatial modeling approach. Transportation Research Part D: Transport and Environment **62**, 212–224 (2018)

[15] Han, Q., Vries, B., Kanters, G.: An agent-based multi-objective optimization model for allocating public charging stations for electric vehicles. In: Proceedings of the 14th International Conference on Computers in Urban Planning and Urban Management, Cambridge, MA, USA, pp. 7–10 (2015)

[16] Unterluggauer, T., Rich, J., Andersen, P.B., Hashemi, S.: Electric vehicle charging infrastructure planning for integrated transportation and power distribution networks: A review. ETransportation **12**, 100163 (2022)

[17] Shukla, R.M., Sengupta, S.: Cop: An integrated communication, optimization, and prediction unit for smart plug-in electric vehicle charging. Internet of Things **9**, 100148 (2020)

[18] Campaña, M., Inga, E.: Optimal deployment of fast-charging stations for electric vehicles considering the sizing of the electrical distribution network and traffic condition. Energy Reports **9**, 5246–5268 (2023)

[19] Zhang, C., Huang, Q., Tian, J., Chen, L., Cao, Y., Zhang, R.: Smart grid facing the new challenge: The management of electric vehicle charging loads. Energy Procedia **12**, 98–103 (2011)

[20] Deb, S., Tammi, K., Kalita, K., Mahanta, P.: Impact of electric vehicle charging station load on distribution network. Energies **11**(1), 178 (2018)

[21] Ul-Haq, A., Cecati, C., Strunz, K., Abbasi, E.: Impact of electric vehicle charging on voltage unbalance in an urban distribution network. Intelligent Industrial Systems **1**, 51–60 (2015)

[22] Tulpule, P.J., Marano, V., Yurkovich, S., Rizzoni, G.: Economic and environmental impacts of a pv powered workplace parking garage charging station. Applied Energy **108**, 323–332 (2013)

[23] Luo, Z., He, F., Lin, X., Wu, J., Li, M.: Joint deployment of charging stations and photovoltaic power plants for electric vehicles. Transportation Research Part D: Transport and Environment **79**, 102247 (2020)

[24] Lai, C.S., Chen, D., Zhang, J., Zhang, X., Xu, X., Taylor, G.A., Lai, L.L.: Profit maximization for large-scale energy storage systems to enable fast ev charging infrastructure in distribution networks. Energy **259**, 124852 (2022)

[25] Zhao, X., Hu, H., Yuan, H., Chu, X.: How does adoption of electric vehicles reduce carbon emissions? evidence from china. Heliyon (2023)

[26] Tsoi, K.H., Loo, B.P., Li, X., Zhang, K.: The co-benefits of electric mobility in reducing traffic noise and chemical air pollution: Insights from a transit-oriented city. Environment International **178**, 108116 (2023)

[27] Liberto, C., Valenti, G., Orchi, S., Lelli, M., Nigro, M., Ferrara, M.: The impact of electric mobility scenarios in large urban areas: The rome case study. IEEE Transactions on Intelligent Transportation Systems **19**(11), 3540–3549 (2018)

[28] Carrese, F., Colombaroni, C., Fusco, G.: Accessibility analysis for urban freight transport with electric vehicles. Transportation Research Procedia **52**, 3–10 (2021)

[29] Ahmad, F., Iqbal, A., Ashraf, I., Marzband, M., *et al.*: Optimal location of electric vehicle charging station and its impact on distribution network: A review. Energy Reports **8**, 2314–2333 (2022)

[30] How much do EV Charging Stations Cost? https://trafficparking.com.au/ev-charging-stations-cost.php. Accessed: 2023-10-05

[31] Mastoi, M.S., Zhuang, S., Munir, H.M., Haris, M., Hassan, M., Usman, M., Bukhari, S.S.H., Ro, J.-S.: An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends. Energy Reports **8**, 11504–11529 (2022)

[32] Justo, J.J., Mwasilu, F., Lee, J., Jung, J.-W.: Ac-microgrids versus dc-microgrids with distributed energy resources: A review. Renewable and sustainable energy reviews **24**, 387–405 (2013)

[33] Κολιός, Κ.: *σχεδιασμός σταθμού ταχείας φόρτισης ηλεκτρικών* οχ*ημάτων με ενσωμάτωση* απε *και συστημάτων α*π*οθήκευσης*. PhD thesis, Α*ριστοτέλει*ο Π*ανε*π*ιστήμι*ο Θ*εσσαλονίκης* (2019)

[34] Illmann, U., Kluge, J.: Public charging infrastructure and the market diffusion of electric vehicles. Transportation Research Part D: Transport and Environment **86**, 102413 (2020)

[35] Khaligh, A., Dusmez, S.: Comprehensive topological analysis of conductive and inductive charging solutions for plug-in electric vehicles. IEEE Transactions on Vehicular Technology **61**(8), 3475–3489 (2012)

[36] Arif, S.M., Lie, T.T., Seet, B.C., Ahsan, S.M., Khan, H.A.: Plug-in electric bus depot charging with pv and ess and their impact on lv feeder. Energies **13**(9), 2139 (2020)

[37] Arif, S.M., Lie, T.T., Seet, B.C., Ayyadi, S.: A novel and cost-efficient energy management system for plug-in electric bus charging depot owners. Electric Power Systems Research **199**, 107413 (2021)

[38] Meishner, F., Satvat, B., Sauer, D.U.: Battery electric buses in european cities: Economic comparison of different technological concepts based on actual demonstrations. In: 2017 IEEE Vehicle Power and Propulsion Conference (VPPC), pp. 1–6 (2017). IEEE

[39] Xiong, J., Zhang, K., Guo, Y., Su, W.: Investigate the impacts of pev charging facilities on integrated electric distribution system and electrified transportation system. IEEE Transactions on Transportation Electrification **1**(2), 178–187 (2015)

[40] Our charging stations are wherever you are at home, at work, in the city, on your trip. https://www.deiblue.com/charging-solutions. Accessed: 2023-10-06

[41] Ahmad, A., Khan, Z.A., Saad Alam, M., Khateeb, S.: A review of the electric vehicle charging techniques, standards, progression and evolution of ev technologies in germany. Smart Science **6**(1), 36–53 (2018)

[42] Erdelić, T., Carić, T., et al.: A survey on the electric vehicle routing problem: variants and solution approaches. Journal of Advanced Transportation **2019** (2019)

[43] Mazhoud, B., Gabet, T., Kadem, K., Meira, Z., Sanzel, A., Coquelle, E., Hornych, P.: Pavement integration of an inductive charging system for electric vehicles. results of the incit-ev project. Transportation Engineering **10**, 100147 (2022)

[44] Chen, F., Taylor, N., Kringos, N.: Electrification of roads: Opportunities and challenges. Applied Energy **150**, 109–119 (2015)

[45] Panchal, C., Stegen, S., Lu, J.: Review of static and dynamic wireless electric vehicle charging system. Engineering science and technology, an international journal **21**(5), 922–937 (2018)

[46] Inci, M., Savrun, M.M., Çelik, Ö.: Integrating electric vehicles as virtual power plants: A comprehensive review on vehicle-to-grid (v2g) concepts, interface topologies, marketing and future prospects. Journal of Energy Storage **55**, 105579 (2022)

[47] Budde-Meiwes, H., Drillkens, J., Lunz, B., Muennix, J., Rothgang, S., Kowal, J., Sauer, D.U.: A review of current automotive battery technology and future prospects. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering **227**(5), 761–776 (2013)

[48] Das, H.S., Tan, C.W., Yatim, A.: Fuel cell hybrid electric vehicles: A review

on power conditioning units and topologies. Renewable and Sustainable Energy Reviews **76**, 268–291 (2017)

[49] Gray, M.K., Morsi, W.G.: Power quality assessment in distribution systems embedded with plug-in hybrid and battery electric vehicles. IEEE Transactions on Power Systems **30**(2), 663–671 (2014)

[50] Roe, C., Farantatos, E., Meisel, J., Meliopoulos, A., Overbye, T.: Power system level impacts of phevs. In: 2009 42nd Hawaii International Conference on System Sciences, pp. 1–10 (2009). IEEE

[51] García-Vázquez, C.A., Llorens-Iborra, F., Fernández-Ramírez, L.M., Sánchez-Sainz, H., Jurado, F.: Comparative study of dynamic wireless charging of electric vehicles in motorway, highway and urban stretches. Energy **137**, 42–57 (2017)

[52] Liu, X., Bie, Z.: Optimal allocation planning for public ev charging station considering ac and dc integrated chargers. Energy Procedia **159**, 382–387 (2019)

[53] Yazdekhasti, A., Jazi, M.A., Ma, J.: Electric vehicle charging station location determination with consideration of routing selection policies and driver's risk preference. Computers & Industrial Engineering **162**, 107674 (2021)

[54] Hakimi, S.L.: Optimum locations of switching centers and the absolute centers and medians of a graph. Operations research **12**(3), 450–459 (1964)

[55] Toregas, C., Swain, R., ReVelle, C., Bergman, L.: The location of emergency service facilities. Operations research **19**(6), 1363–1373 (1971)

[56] Church, R., ReVelle, C.: The maximal covering location problem. In: Papers of the Regional Science Association, vol. 32, pp. 101–118 (1974). Springer-Verlag Berlin/Heidelberg

[57] Hodgson, M.J.: A flow-capturing location-allocation model. Geographical analysis **22**(3), 270–279 (1990)

[58] Sun, Z., Gao, W., Li, B., Wang, L.: Locating charging stations for electric vehicles. Transport Policy **98**, 48–54 (2020)

[59] Xiong, Y., Gan, J., An, B., Miao, C., Bazzan, A.L.: Optimal electric vehicle fast charging station placement based on game theoretical framework. IEEE Transactions on Intelligent Transportation Systems **19**(8), 2493–2504 (2017)

[60] Zhu, Z.-H., Gao, Z.-Y., Zheng, J.-F., Du, H.-M.: Charging station location problem of plug-in electric vehicles. Journal of Transport Geography **52**, 11–22 (2016)

[61] Ahangar, S.S., Abazari, S.R., Rabbani, M.: A region-based model for optimizing charging station location problem of electric vehicles considering disruption-a case

study. Journal of cleaner production **336**, 130433 (2022)

[62] Islam, M.M., Shareef, H., Mohamed, A.: Optimal location and sizing of fast charging stations for electric vehicles by incorporating traffic and power networks. IET Intelligent Transport Systems **12**(8), 947–957 (2018)

[63] Sadeghi-Barzani, P., Rajabi-Ghahnavieh, A., Kazemi-Karegar, H.: Optimal fast charging station placing and sizing. Applied Energy **125**, 289–299 (2014) https://doi.org/10.1016/j.apenergy.2014.03.077 . Cited by: 364

[64] Mohsenzadeh, A., Pazouki, S., Ardalan, S., Haghifam, M.-R.: Optimal placing and sizing of parking lots including different levels of charging stations in electric distribution networks. International Journal of Ambient Energy **39**(7), 743–750 (2018)

[65] He, Y., Song, Z., Liu, Z.: Fast-charging station deployment for battery electric bus systems considering electricity demand charges. Sustainable Cities and Society **48**, 101530 (2019)

[66] Zhou, G., Zhu, Z., Luo, S.: Location optimization of electric vehicle charging stations: Based on cost model and genetic algorithm. Energy **247**, 123437 (2022)

[67] Ma, T.-Y., Xie, S.: Optimal fast charging station locations for electric ridesharing with vehicle-charging station assignment. Transportation Research Part D: Transport and Environment **90**, 102682 (2021)

[68] Wang, Y., Shi, J., Wang, R., Liu, Z., Wang, L.: Siting and sizing of fast charging stations in highway network with budget constraint. Applied Energy **228**, 1255–1271 (2018)

[69] Moradi, M.H., Abedini, M., Tousi, S.R., Hosseinian, S.M.: Optimal siting and sizing of renewable energy sources and charging stations simultaneously based on differential evolution algorithm. International Journal of Electrical Power & Energy Systems **73**, 1015–1024 (2015)

[70] Napoli, G., Polimeni, A., Micari, S., Andaloro, L., Antonucci, V.: Optimal allocation of electric vehicle charging stations in a highway network: Part 1. methodology and test application. Journal of Energy Storage **27**, 101102 (2020)

[71] Luo, L., Wu, Z., Gu, W., Huang, H., Gao, S., Han, J.: Coordinated allocation of distributed generation resources and electric vehicle charging stations in distribution systems with vehicle-to-grid interaction. Energy **192**, 116631 (2020)

[72] Balakrishna, P., Rajagopal, K., Swarup, K.: Ami/gis based distribution system load flow for extended situational awareness. In: 2014 Eighteenth National Power Systems Conference (NPSC), pp. 1–6 (2014). IEEE

[73] Bouguerra, S., Layeb, S.B.: Determining optimal deployment of electric vehicles charging stations: Case of tunis city, tunisia. Case Studies on Transport Policy **7**(3), 628–642 (2019)

[74] Zeng, T., Bae, S., Travacca, B., Moura, S.: Inducing human behavior to maximize operation performance at pev charging station. IEEE Transactions on Smart Grid **12**(4), 3353–3363 (2021)

[75] Ge, S., Feng, L., Liu, H.: The planning of electric vehicle charging station based on grid partition method. In: 2011 International Conference on Electrical and Control Engineering, pp. 2726–2730 (2011). IEEE

[76] Frade, I., Ribeiro, A., Goncalves, G., Antunes, A.: An optimization model for locating electric vehicle charging stations in central urban areas. compendium of papers dvd of trb 90th annual meeting. Transportation Research Board (2010)

[77] Li, Y., Li, L., Yong, J., Yao, Y., Li, Z.: Layout planning of electrical vehicle charging stations based on genetic algorithm. In: Electrical Power Systems and Computers: Selected Papers from the 2011 International Conference on Electric and Electronics (EEIC 2011) in Nanchang, China on June 20–22, 2011, Volume 3, pp. 661–668 (2011). Springer

[78] Hanabusa, H., Horiguchi, R.: A study of the analytical method for the location planning of charging stations for electric vehicles. In: Knowledge-Based and Intelligent Information and Engineering Systems: 15th International Conference, KES 2011, Kaiserslautern, Germany, September 12-14, 2011, Proceedings, Part III 15, pp. 596–605 (2011). Springer

[79] Jia, L., Hu, Z., Song, Y., Luo, Z.: Optimal siting and sizing of electric vehicle charging stations. In: 2012 IEEE International Electric Vehicle Conference, pp. 1–6 (2012). IEEE

[80] Liu, Z.-f., Zhang, W., Ji, X., Li, K.: Optimal planning of charging station for electric vehicle based on particle swarm optimization. In: IEEE PES Innovative Smart Grid Technologies, pp. 1–5 (2012). IEEE

[81] Wang, G., Xu, Z., Wen, F., Wong, K.P.: Traffic-constrained multiobjective planning of electric-vehicle charging stations. IEEE Transactions on Power Delivery **28**(4), 2363–2372 (2013)

[82] Schiffer, M., Stütz, S., Walther, G.: Are ecvs breaking even?-competitiveness of electric commercial vehicles in medium-duty logistics networks. RWTH Aachen Univ., Aachen, Germany, Work. Paper OM-02/2016 (2016)

[83] Schiffer, M., Walther, G.: The electric location routing problem with time windows and partial recharging. European journal of operational research **260**(3), 995–1013 (2017)

[84] Tang, X., Bi, S., Zhang, Y.-J.A.: Distributed routing and charging scheduling optimization for internet of electric vehicles. IEEE Internet of Things Journal **6**(1), 136–148 (2018)

[85] Kınay, Ö.B., Gzara, F., Alumur, S.A.: Full cover charging station location problem with routing. Transportation Research Part B: Methodological **144**, 1–22 (2021)

[86] Göpfert, P., Bock, S.: A branch&cut approach to recharging and refueling infrastructure planning. European Journal of Operational Research **279**(3), 808–823 (2019)

[87] Alonso, G., Del Valle, E., Ramirez, J.R.: Desalination in Nuclear Power Plants, (2020)

[88] Bazaraa, M.S., Sherali, H.D., Shetty, C.M.: Nonlinear Programming: Theory and Algorithms, (2013)

[89] Ceria, S., Cordier, C., Marchand, H., Wolsey, L.A.: Cutting planes for integer programs with general integer variables. Mathematical programming **81**, 201–214 (1998)

[90] Nocedal, J., Wright, S.J.: Quadratic programming. Numerical optimization, 448–492 (2006)

[91] Wolsey, L.A., Nemhauser, G.L.: Integer and Combinatorial Optimization vol. 55, (1999)

[92] Bertsekas, D.: Dynamic Programming and Optimal Control: Volume I vol. 4, (2012)

[93] Wen, M., Larsen, J., Clausen, J., Cordeau, J.-F., Laporte, G.: Vehicle routing with cross-docking. Journal of the Operational Research Society **60**, 1708–1718 (2009)

Appendix

Model Formulation

```
import gurobipy as gp
import matplotlib
from gurobipy import GRB
import random
import  math
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import style
import matplotlib
matplotlib.use('TkAgg')

numberoflocations = 150
numberofstations = 50
numberofnodes = numberoflocations+numberofstations
typesofvehicles = 2
numberofdrivers = 1000
data = 'e'

Mbig=10000 #a large positive number

#SETS
drivers = (r for r in range(1, numberofdrivers+1))
drivers = tuple(drivers)

locations = (r for r in range(1, numberoflocations+1))
locations = tuple(locations)

stations = (r for r in range(1, numberofstations+1))
stations = tuple(stations)

#PARAMETERS
#for i in drivers:
#    p = {i:random.randint(1,numberoflocations)}
#    print(p[i])

# p = {1:1, 2:1, 3:1, 4:2, 5:2, 6:3, 7:4, 8:5, 9:6, 10:6}

vehiclestype = (1,2)


#TD = {r:random.randint(1000,5000) for r in drivers}
TD = {r:60 for r in drivers}
#VQk = {k:random.randint(10,20) for k in vehiclestype}
VQk = {1:70, 2:200}
#100-300kwh for medium
#30-100kwh for light
#StationCapacity = (numberofdrivers/numberofstations) * 1.1 * 250
StationCapacity = 6000
print('Station Capacity:')
print( StationCapacity)
```

```
#totalbudget = 10000*numberofstations*2/3*25
totalbudget = 10000000
print( totalbudget)
#Cost = {j: random.randint(1000,3000) for j in stations}
Cost ={j:4000 for j in stations}
#10000 euros for a unit (approx. 3000euros per year for
maintenance)

filename1 = 'Instances/Data_L_' + str(numberoflocations) + '_S_' +
str(numberofstations) +'_'+ data +'.txt'

DataX_a= filename1
data_header=np.loadtxt(DataX_a,max_rows=1,dtype=int)
data_header_decimal=np.loadtxt(DataX_a,max_rows=1,dtype=float)
data_main_body=np.loadtxt(DataX_a,skiprows=1,dtype=int)

n=data_header[0]
#read coordinates
latitudeLocations = {}; longitudeLocations ={}
latitudeStations = {}; longitudeStations ={}
q={}; d={}

for i in locations:
      latitudeLocations[i]=data_main_body[i,3]
      longitudeLocations[i]=data_main_body[i,4]


for j in stations:
      latitudeStations[j]=data_main_body[numberoflocations+j,3]
      longitudeStations[j]=data_main_body[numberoflocations+j,4]

MinDistance = -1;
MaxDistance = 0;
d={};t={}; the_distance={}
from scipy.spatial import distance
for i in locations:
    for j in stations:
        d[(i,j)] =
(1/1000)*distance.euclidean([latitudeLocations[i],longitudeLocatio
ns[i]],[latitudeStations[j],longitudeStations[j]]) *
(60/data_header[4])
        if d[(i,j)] > MinDistance:
            MaxDistance = d[(i,j)]
            MinDistance = d[(i,j)]


print(MaxDistance/3)

filename2 = 'Instances/Data_L_' + str(numberoflocations) + '_S_' +
str(numberofstations) +  '_D_' +str(numberofdrivers) +'_'+ data
+'_DriversInfo.txt'
DataX_b= filename2
data_header=np.loadtxt(DataX_b,max_rows=1,dtype=int)
data_header_decimal=np.loadtxt(DataX_b,max_rows=1,dtype=float)
```

```
data_main_body=np.loadtxt(DataX_b,skiprows= 1, dtype=int)

p = {}
mrk = {}
for i in drivers:
    p[i] = data_main_body[i, 1]
    vehicleType = data_main_body[i, 2]
    if vehicleType == 1:
        mrk[i,1] = 1
        mrk[i, 2]  =  0
    if vehicleType == 2:
        mrk[i, 1] = 0
        mrk[i, 2] = 1

print('NOT FOUND LOCATIONS------------------ ')
for k in range(1,numberoflocations):
    Notfound = True
    for i in drivers:
        if k == p[i]:
            Notfound = False
            continue
    if (Notfound == True):
        print(k)

# Initialize the Gurobi model
model = gp.Model()

# VARIABLES
numberofchargers = model.addVars(stations,vtype=GRB.INTEGER,
name="numberofchargers") #n_j
open = model.addVars(stations,vtype=GRB.BINARY,name="open") #x_j
assign =
model.addVars(drivers,stations,vtype=GRB.BINARY,name="assign")#y_r
j

# CONSTRAINTS
model.addConstrs(sum(assign[r, j] for j in stations) == 1 for r in
drivers)
model.addConstrs(numberofchargers[j] >= 0 for j in stations)
model.addConstrs(open[j] >= assign[r,j] for r in drivers for j in
stations)
model.addConstrs(open[j] <= numberofchargers[j] for j in stations)
model.addConstrs(numberofchargers[j] <= Mbig * open[j] for j in
stations)
model.addConstrs(sum(assign[r,j] for r in drivers) ==
numberofchargers[j] for j in stations)
model.addConstrs(d[p[r],j] * assign[r,j] <= TD[r] for r in drivers
for j in stations)
model.addConstr(sum(Cost[j] * numberofchargers[j] for j in
stations)  <=  totalbudget)
model.addConstrs(sum(sum(assign[r,j]* mrk[r,k]* VQk[k] for k in
vehiclestype) for r in drivers) <= StationCapacity for j in
stations)
```

```
model.setObjective(sum(sum(d[p[r],j]* assign[r,j] for r in
drivers) for j in stations), GRB.MINIMIZE)
model.optimize()

if model.status == GRB.OPTIMAL: # check if the solver is capable
of finding an optimal solution
      model.printAttr('X')
      print(model.status, 'optimal')
      print('Obj: %g' % model.objVal)
else:
      print(model.status, 'not optimal')


model.printAttr('x')

for i in locations:
    plt.scatter(latitudeLocations[i], longitudeLocations[i],
c="black",
            linewidths=2,
            marker="s",
            edgecolor="black",
            s=70)
    plt.text(latitudeLocations[i], longitudeLocations[i]*1.0001,
i, va='bottom', ha='center', fontsize=15)

for j in stations:
    # if (open[j] >= 1):
        plt.scatter(latitudeStations[j], longitudeStations[j],
            c="grey",
            linewidths=2,
            marker="^",
            edgecolor="grey",
            s=70)
        plt.text(latitudeStations[j], longitudeStations[j]*1.0001,
j,va='bottom', ha='center', fontsize=15)
    # else:
        plt.scatter(latitudeStations[j], longitudeStations[j],
                    c="grey",
                    linewidths=2,
                    marker="^",
                    edgecolor="grey",
                    s=70)
        plt.text(latitudeStations[j], longitudeStations[j] *
1.0001, j, va='bottom', ha='center', fontsize=15)

plt.xlabel("X-axis")
plt.ylabel("Y-axis")
averageNumberOfChargers = 0
numberOfOpenStations = 0
for j in stations:
    if (open[j]):
        averageNumberOfChargers += numberofchargers[j].X
        numberOfOpenStations += open[j].X
averageNumberOfChargers = averageNumberOfChargers /
```

```
numberOfOpenStations

print('FINAL RESULTS')
print( '%.2f' % model.objVal , '%.2f' % model.objBound , '%.2f' %
model.MIPGap, '%.2f' % model.Runtime, '%.2f' %
averageNumberOfChargers,  '%.2f' % numberOfOpenStations)
plt.show()

style.use("ggplot")`
```