ROBUST DESIGN OF ELECTRIC CHARGING INFRASTRUCTURE LOCATIONS UNDER TRAVEL DEMAND UNCERTAINTY AND DRIVING RANGE HETEROGENEITY

by

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To my family.

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NOTATIONS

A: Set of links

$\breve{A}$: Set of dummy links

B^t: Construction budget for charging stations in period t

$Z_{r,s}^{m,t}$: Set of travel demand uncertainty of vehicle class m for each O-D pair (r,s) in period t

H_1: Total system travel time

H_2: Total penalty of unused charging station capacity

$K_{r,s}^{m,t}$: Set of paths of each vehicle class m for each O-D pair (r,s) in each period t

$L_{i,j}$: Length of link (i,j)

M: Set of vehicle classes

N: Set of nodes

$\bar{\bar{N}}$: Set of dummy nodes with existing refueling stations

$\bar{N}$: Set of dummy candidate nodes for construction of charging stations

$\breve{N}$: Set of dummy nodes with existing charging stations

Q: Travel demand uncertainty set

$R^{m,t}$: driving range of class m vehicle in period t

W: Set of O-D pairs

$c_{i,j}^t$: Delay for link (i,j) in period t

$\hat{c}_{j,j'}^{m,t}$: Pseudo delay of dummy link (j,j') for class m in period t

$e_{ij}^{w,m,t}$: Binary variable that determines whether link (i,j) is a part of feasible path of travelers between O-D pair w for class m in period t

NOTATIONS (CONTINUED)

$f_{i,j}^{w,t,m}$: Flow of vehicle class m travelers of O-D pair w between link (i, j) in period t

$\bar{h}_j$: Minimum acceptable refueling demand to maintain refueling station j

k_i^t: Construction cost of charging station of node i at period t

n_j: Charging/refueling capacity of charging/refueling station at node j

$p_{r,s}^{m,e,t}$: Binary variable that indicates whether scenario e is realized for vehicle class m of O-D pair (r, s) in period t

$q_{r,s}^{m,e,t}$: Travel demand of vehicle class m of O-D pair (r, s) under scenario e in period t

$q_{r,s}^{e,t}$: Aggregate travel demand of O-D pair (r, s) under scenario e in period t

$q_{r,s}^{m,t}$: Realized travel demand of vehicle class m of O-D pair (r, s) in period t

$u_i^{w,m,t}$: Traveler distance just before visiting node i from the last-visited charging station for travelers of O-D pair w for class m in period t

$u'^{w,m,t}_i$: Traveler distance after visiting node i from the last-visited charging station for travelers of O-D pair w for class m in period t

$v_{i,j}^t$: Traffic flow of link (i, j) in period t

τ: Set of periods

$\Omega(\boldsymbol{q})$: UE link flows for each $\boldsymbol{q}$

ϕ_1: Weight of total system travel time

ϕ_2: Weight of total penalty of unused chargers in the objective function

β^t: Value of time of travelers in period t

NOTATIONS (CONTINUED)

$\delta_{k,i,j,r,s}^{m,t}$: Path indicator, 1 if the link (i,j) is on path k for vehicle class m travelers of O-D pair (r,s) in period t, and 0 otherwise

Γ^t: Uncertainty budget in period t

Ψ: Penalty for unused charging station capacity

Δ^t: Conversion factor to calculate the present value of cost of period t

κ: Conversion factor for travelers' travel cost and unused charging station capacity

π: Constant interest rate

Λ: A sufficiently large number

$\varsigma_{i,j}$: Binary variable, 1 if link (i,j) belongs to the shortest path, and 0 otherwise

χ_i: Remaining charge or fuel level at node i after recharging or refueling, respectively

Υ_i: The recharging or refueling amount at node i

$\rho_{i,j}$: Auxiliary variable, 0 if link (i,j) belongs to the shortest path, 1 otherwise

$\varrho_i^{m,t}$: Maximum refueling or recharging amount that can be provided at node i for vehicle class m in period t

φ_i^t: Operation status of refueling station at node i and period t

θ_i^t: Operation status of charging station at node i and period t

$\mu_i^{w,t,m}$: Travel time of travelers of O-D pair w for class m at node i and in period t

$\zeta_{ij}^{w,t,m}$: Imposed excessive travel time between link (i,j) for travelers of class m between O-D pair w at period t

$\bar{n}_i$: capacity of charging station i

LIST OF ACRONYMS

BEV	Battery Electric Vehicles
CAV	Connected and Autonomous Vehicle
EV	Electric Vehicles
ER-EVs	Extended-range Electric Vehicles
FCEVs	Fuel Cell Electric Vehicles
GPS	Global Positioning System
HEVs	Hybrid Electric Vehicles
ICEV	Internal Combustion Engine Vehicle
NGSA-II	Non-dominated Sorting Genetic Algorithm II
O-D	Origin-Destination
PHEVs	Plug-In Hybrid Electric Vehicles
SoC	State of Charge
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WCL	Wireless Charging Lanes
WPT	Wireless Power Transfer

LIST OF COMMONLY USED TERMS

Transportation decision-maker	A road agency that owns the roadway infrastructure. This agency is responsible for constructing electric charging facilities. In some cases, charging facility types are provided by a private-sector entity through lease, through design-build-operate contracting, or as infrastructure owned/operated independently of the road network. In such cases, the transportation decision-maker is the road agency that makes the investment decisions in conjunction with the private-sector entity.
EV charging facility planning	Long-term decision-making on electric charging infrastructure, regarding location, year of installation/construction, and charging capacity.
Traffic network user equilibrium	Users of a congested road network, seeking to determine their travel paths of minimal cost from their origins to their respective destinations, choose their most convenient path selfishly. At equilibrium, the number of trips between an origin and a destination equals the travel demand given by the market price (i.e., the travel time for the trips), and all users sharing the same origin and destination experience the same travel time.
Dynamic charging	Charging an EV while it is moving.
Charging station	Equipment that connects an EV to a source of electricity to recharge it using a connector (cable).
Charging station capacity	Number of travelers that can use the EV charging station per unit of time.
EV driving range	The estimated distance an EV can drive at a given quantity of battery level.
EV charging facility method	Static or dynamic charging.
Static charging	A method of charging an EV that requires the EV to be still.
Wireless charging lane	Equipment that recharges an EV without a connector (cable) while the EV is moving.
Market penetration	Measure of how many EVs/ICEVs are being purchased by travelers.

ABSTRACT

The rising demand for EVs, motivated by their environmental benefits, is generating increased need for EV charging infrastructure. Also, it has been recognized that the adequacy of such infrastructure helps promote EV use. Therefore, to facilitate EV adoption, governments seek guidance on continued investments in EV charging infrastructure development. The high cost of these investments motivates governments to seek optimal decisions on EV-related investments including EV charging infrastructure, and such decisions include locations, capacities, and deployment scheduling of such infrastructure. Additionally, uncertainties in travel demand prediction and EV driving range constraints need to be considered in EV infrastructure investment planning. To help address these questions, this thesis developed a framework to establish optimal schedules and locations for new charging stations and for decommissioning gasoline refueling stations for any given network over a long-term planning horizon, considering uncertainties in travel demand forecasts and EV driving-range heterogeneity. To address the uncertainties, the proposed framework is formulated as a robust mathematical model that minimizes the worst-case total system travel cost and the total penalty for unused charging station capacity. This study uses an adaption of the cutting-plane method to solve the proposed model. In the numerical analyses, the performance of the robust framework and its deterministic counterpart are compared. The results show that the optimal robust plan outperforms the deterministic plan by yielding savings in the costs of travel and electricity charging. The thesis also investigates the effects of investment budget levels of robust planning. The numerical results throw light on the relationships between higher investment levels and electric charging station deployment levels and consequently, the savings in travel costs and impacts on unused charging capacity. The outcomes of this thesis can help road agencies and related private sector entities enhance preparations towards infrastructure investments to support electric charging stations in an efficient manner.

CHAPTER 1 INTRODUCTION

1.1 Background

Global concerns associated with the environment, climate change, and energy security continue to motivate the transition from fossil fuel vehicles (also referred to as internal combustion engine vehicles; ICEV) to other fuel types. Of the various types of alternative fuel vehicles, electric vehicles (EVs) have been proven to be a viable option to replace ICEVs.

To support the ICEV–EV transition, governments and automakers globally continue to make efforts, through policy and design, to increase the EV market share. For example, the United Kingdom and France seek to end ICEV sales by 2040 (Racherla & Waight, 2018). Despite global efforts, the current BEV market share is still limited worldwide. For example, according to recent data, the EV market share is less than 2% in the United States, even though several incentive programs to promote EVs have been implemented (Alternative Fuels Data Center, 2022; Highway Statistics Series, 2022). However, the number of EV sales is growing. It is reported that in the third quarter of 2023, total sales of EVs rose to around 7.9% of the brand-new vehicle market in the US (CarEdge, 2023).

The lack of electric charging stations is well recognized as one of the barriers to EV adoption in the US (Indiana Department of Transportation, 2022; Michigan Department of Transportation, 2022; New York Department of Transportation, 2022; Texas Department of Transportation, 2022). Researchers have found that in addition to initiatives including enhancements to battery capacity, reduction of recharging time, and increase in time-to-depletion, the provision of adequate electric charging stations helps reduce the driving range anxiety of EV users and ultimately promotes the EV penetration rate in the US (Cihat Onat et al., 2018; Coffman et al., 2016; Desai et al., 2021; Fauble et al., 2022; Funke et al., 2019; Huang & Kockelman, 2020). Based on the ongoing efforts in EV adaption, it is expected that the share of EVs in the sales market will grow over time and jump to around 30% in 2023 (EVAdoption, 2023). Figure 1.1 shows a projection of the total sales of EVs in the US market over the next 10 years.

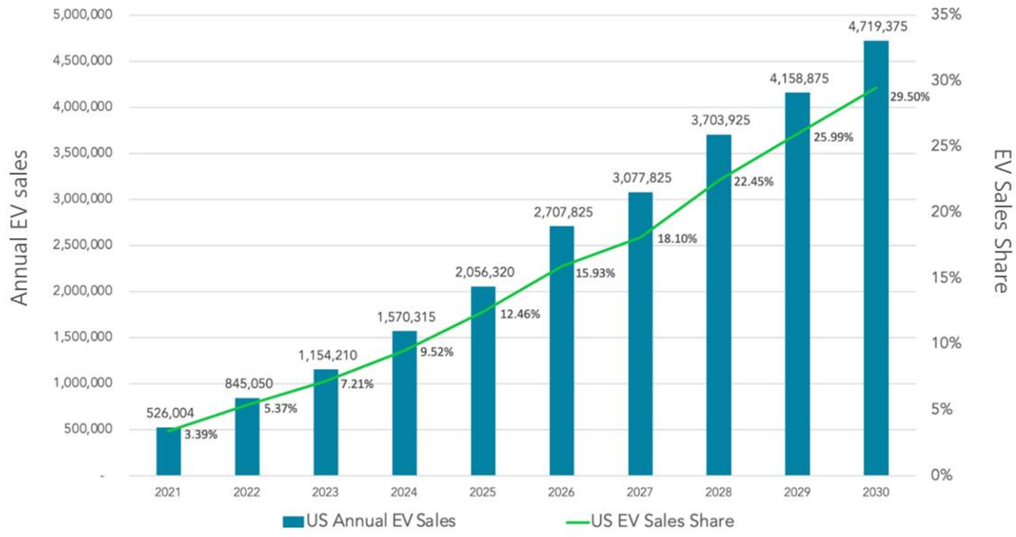

Figure 1.1. EV sales share prediction in US market (EVAdoption, 2023)

Franke and Krems (2013) argued that unless public authorities and private entities provide adequate charging stations to satisfy EV charging demand, customers will not be willing to purchase EVs. Due to the importance of charging stations, the US government recently provided a $5-billion budget for building EV charging infrastructure across the nation’s highway network (FHWA, 2022).

Such promotion of EVs is considered urgent in the current era for at least two reasons. First, the reduction of greenhouse gases is a major goal of the Infrastructure Investment and Jobs Act (IIJA; Public Law 117-58), an unprecedented piece of transportation legislation signed by President Biden in 2021. That legislation specifically targets climate change and therefore requires the Federal Energy Regulatory Commission to require each state to consider measures to promote greater transportation electrification, including the promotion of EV charging and improvement of the customer experience with EV charging. With their zero-emissions feature, EVs are more environmentally friendly and pose less threat to the climate and therefore are of great interest to both public agencies and road users concerned with their environmental impact (Gardner et al., 2013). Second, the shift from gasoline to electric propulsion is part of the broader national goal of energy security, an issue that has gained prominence in the wake of the Russia-Ukraine war.

Similar to all infrastructure systems, the development of EV charging infrastructure must balance investment level and usage. On the one hand, inadequate charging stations will cause delays and frustration for EV users; on the other hand, an excessive number of stations will lead to excess idle time, underutilization of the stations, and, ultimately, a waste of resources. Constructing adequate electric stations at well-chosen locations will decrease driving range anxiety and, therefore, is paramount to facilitating EV promotion (Cihat Onat et al., 2018; Coffman et al., 2016; Desai et al., 2021; Fauble et al., 2022; Funke et al., 2019; F. Guo et al., 2018; Huang and Kockelman, 2020). From a broader perspective of infrastructure management, urban infrastructure investment planning to promote EVs should first ensure that adequate levels of service are consistently maintained for the customers (Kielhauser et al., 2017) (in the context of this thesis, the customers are the EV users, and level of service refers to range anxiety). Second, it should consider uncertainty and risk in the investment analysis inputs (Kielhauser and Adey, 2016).

1.2 Electric Vehicle Types

Different types of EVs have been introduced in the vehicle manufacturing industry. These EVs differ mainly based on electricity storage technology, electric recharging type, and propulsion force source. In this subsection, EV types and their important characteristics are introduced:

- Battery electric vehicles (BEVs): There is no internal combustion engine in BEVs, and BEVs do not use any sort of liquid fuel. Therefore, BEVs are propelled only by electricity. Different BEVs have different driving ranges that range from approximately 100 to 300 miles (Das et al., 2020; Sanguesa et al., 2021).
- Plug-in hybrid electric vehicles (PHEVs): This type of EV takes advantage of the hybrid propulsion mechanism of an internal combustion engine and electricity power. PHEVs can be recharged by available electricity charging facilities (Das et al., 2020; Sanguesa et al., 2021).
- Hybrid electric vehicles (HEVs): HEVs have the same propulsion mechanism as PHEVs: a combination of a conventional internal engine and electricity power. However, HEVs are different from PHEVs regarding the battery charging process. HEVs' batteries are not recharged through available electricity charging facilities. Instead, the batteries in HEVs are charged by the power generated by the internal combustion engine. For example, some HEVs are able to generate electricity during braking (Das et al., 2020; Sanguesa et al., 2021).

- Fuel cell electric vehicles (FCEVs): FCEVs burn compressed hydrogen to generate energy, and the generated energy is further converted to electricity. Water is the only material produced as a result of this process. FCEVs cannot be charged by currently available charging facilities (Das et al., 2020; Sanguesa et al., 2021).
- Extended-range electric vehicles (ER-EVs): ER-EVs are similar to BEVs; however, they are equipped with combustion engines used for battery charging. More specifically, the combustion engine does not generate any propulsion power and is not connected to the wheels (unlike HEVs and PHEVs, which use internal combustion engines to generate propulsion power too) (Das et al., 2020; Sanguesa et al., 2021).

1.3 Electric Charging Facilities

Three mechanisms for EV charging have been discussed in the literature: (i) static charging (using charging stations), (ii) inductive/wireless charging (Chen et al., 2016), and (iii) battery swapping (Adler et al., 2016). In the following, static and wireless charging are introduced in more detail.

Based on the power level of the charging equipment, the static charging method can be classified further into three levels. Level 1 charges EVs using 120-volt AC outlets, which is the lowest available voltage level in residential and business buildings in the US. So, level 1 is suitable for residential locations. Level 1 is a cheapest charging facility and can be set up at residential locations without any further required infrastructure. As level 1 provides a small amount of power, the charging duration is relatively long and can reach 20 hours (Morrow et al., 2008; Khalid et al., 2021; Kakkar et al., 2022). Level 2 provides a voltage of 240 volts for commercial AC electrical services. Due to the higher power provided, users can charge their EVs in a shorter time (around a few hours). Level 2 is suitable for public parking or residential buildings (Morrow et al., 2008; Khalid et al., 2021; Kakkar et al., 2022). Level 3 uses 480-volt AC power service and is referred to as “DC fast charging.” Level 3 is suitable for both public and commercial applications and is similar to a gas service station. The charging duration with level 3 charging is less than one hour (Morrow et al., 2008; Khalid et al., 2021; Kakkar et al., 2022).

Wireless charging takes advantage of electromagnetic fields to provide conductive charging for EVs. Through this method, EV users can charge EVs wirelessly, without any cable connection. Three types of wireless charging have been developed. The first is stationary wireless charging, which provides conductive charging at a static location (Das et al., 2020). The second is dynamic wireless charging, which enables EV users to charge their vehicles while they are driving. Therefore, they do not need stop at any charging stations (Das et al., 2020). The last type of wireless charging is quasi-dynamic wireless charging. With this technology, EVs can still charge in motion but at a slower speed than dynamic wireless charging (Das et al., 2020).

1.4 Problem Statement

There is a need to determine a model for the optimal location of level-3 electric charging stations in order to satisfy the charging demand of travelers for intercity trips during the transition period on the path toward full EV fleet market share. Due to their fast-charging technology, these types of EV charging stations are suitable for rural networks. Therefore, travelers can charge their EVs in a few minutes and continue their journeys. In addition to prospective new locations for the construction of electric charging stations, current gasoline (including diesel) refueling stations serve as candidate locations for installing EV charging stations. However, it is expected that ICEVs (which patronize gasoline refueling stations) will continue to constitute a major part of the roadway traffic fleet during most of the transition period. Therefore, their refueling needs will have to be addressed. As the market share of ICEVs decreases during the transition period, an increasing number of gasoline refueling stations will experience low demand and ultimately become candidates for decommissioning or repurposing as EV charging stations. In this study, therefore, it is assumed that refueling stations are decommissioned only when their demand falls below a certain threshold. Moreover, there is great variability in the driving ranges across the different EV classes and across different manufacturers. For example, the driving ranges of the Nissan Leaf and Tesla Model X are approximately 150 and 300 miles, respectively (Insideevs, 2018). As such, this study accounts for the driving range heterogeneity of EVs.

In practice, the task of locating EV charging infrastructure on a road network has been identified as a constituent aspect of the strategic plans of service providers and governments over long planning horizons. Due to the long-term horizon that is typical of agency strategic plans, the service provider needs to carry out a strategic network design that accommodates EV charging demand. Such demand is influenced by the EV adoption rate and the driving behavior of travelers. Over the next few decades, the EV adoption rate is generally expected to increase, but the rate of increase is uncertain due to factors including initial price sensitivity, energy cost, range reliability, and charging infrastructure availability (Liu & Lin, 2016). Further, fast-growing technological advancements and disruptive technologies, including electric automated vehicles, are expected to exacerbate the uncertainty in travel demand and driving patterns over the next few decades. Given the uncertainty in the EV adoption rate and driving behavior, it can be argued that EV charging demand can also be expected to be highly uncertain.

1.5 Problem Objectives

This study seeks to duly and explicitly consider the uncertainty in EV charging demand over a long-term planning horizon (that is, on the order of several years) to locate EV charging stations to serve intercity travel. As stated earlier, the uncertainty in electric charging demand can be attributed to uncertainty in travel demand forecasts over a long-term planning horizon. In practice, there is inherent uncertainty in forecasting travel demand over a long-term planning horizon, and the accuracy of travel demand forecasts declines with the length of the planning horizon. In other words, near-term travel demand forecasts are more accurate or reliable compared to medium- or long-term forecasts. This demand uncertainty could be attributed to changes in land use or economic and demographic characteristics. However, this has not been addressed in the context of EV charging station location and therefore represents another gap in the literature. In mathematical programming, there are two methods to address such uncertainty. The first, stochastic programming, assumes different probabilities of occurrence for different scenarios (Dantzig, 1955). However, estimating this probability distribution is difficult in practice. The second method proposes the concept of a robust approach that optimizes the system against the worst-case scenario while circumventing the need to estimate the probabilities of different scenarios (Bertsimas & Sim, 2003). This has been applied previously for network design with demand uncertainty (Lou et al., 2009). In this study, the second method is adopted as it seeks to develop a robust design of EV charging station locations under travel demand uncertainty. This study formulates this as a multiobjective optimization problem that seeks to reduce the maximum total system travel time and the costs associated with unused charging station capacity over a long planning horizon.

In summary, the objectives of this study in relation to the literature are as follows: This study seeks to develop a robust design for a network of electric charging stations to address the uncertainty of travelers' refueling and electric charging demands. The study also seeks to develop a framework that prepares the charging infrastructure during the transition stage by gradually decommissioning existing refueling stations in the context of intercity trips. The third contribution is the consideration of the driving range heterogeneity of EV batteries.

1.6 Scope of the Study

This thesis considers electric charging station planning from the perspective of two key stakeholders: the owner (an urban road agency) and EV users. As Adey (2018) pointed out, the management of any infrastructure should address effectiveness and efficiency goals from the perspectives of the key stakeholders. In this regard, the urban road agency, a key stakeholder in the analysis of this thesis, provides the investment resources for deploying the electric charging stations. The objectives of this stakeholder and of the EV users include effectiveness in terms of and efficiency in terms of EV facility deployment expenditure, EV users’ travel-time cost, EV charging station capacity underutilization, and fees paid by the EV users. The electric charging stations to be deployed are Level 3 fast charging and are open to all EV users without any restrictions. In its investment planning framework, this thesis does not present or capture a demand prediction model.

1.7 Organization of the Thesis

The remaining sections are structured as follows: Section 2 presents a literature review on EV charging station planning. Next, the proposed methodology and solution algorithm are introduced in Section 3. Section 4 discusses the numerical experiments that compare the performances of robust and deterministic designs of electric charging station locations under travel demand uncertainty forecasts. Finally, the study’s insights and concluding remarks are provided in Section 5.

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CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

EV charging facilities supply electrical energy for charging EVs, and, therefore, the operation of EVs depends on them. It is important to make effective decisions on constructing new facilities to promote EV adoption. These decisions involve many aspects of EV charging facilities, such as the types of charging facilities, their locations, and their charging levels. There are three levels of EV charging facilities: level 1, level 2, and level 3. These levels of EV charging facilities are mainly different in the output electricity power provided. In this regard, levels 1 and 2 are known as slow charging, and level 3 is called fast charging. Some studies have focused on slow EV charging facilities (i.e., Frade et al., 2011; Jia et al., 2014). For example, Frade et al. (2011) proposed a model for locating slow-charging facilities to maximize demand coverage while keeping the service level within an acceptable range. The majority of the studies in the literature have focused on fast-charging facility planning (i.e., Miralinaghi, Keskin, et al., 2016; Amjad et al., 2018; Domínguez-Navarro et al., 2019; Kchaou-Boujelben and Gicquel, 2020; Jordan et al., 2022; Tungom et al., 2023). As the focus of this study is the locating of charging stations, this chapter includes a literature review on electric charging facility locating problems. First, a brief overview of different levels of electric charging stations is presented. Next, the studies on fast (or level 3) electric charging stations are reviewed in two subsections: deterministic and uncertain demand assumptions. And last, a review of wireless electric charging lanes is presented.

2.2 Electric Charging Location Problems

There is an extensive body of research on EV charging station planning. These studies have covered different aspects, including charging technologies (Brenna et al., 2020; Fisher et al., 2014; Shevchenko et al., 2019); travelers' behaviors and preferences in electrification (Y. Guo et al., 2021, 2022); and optimal charging station configuration (Bai et al., 2019; Kchaou-Boujelben & Gicquel, 2020; Kınay et al., 2021; Yıldız et al., 2019). This study relates to only the past studies on optimal charging station planning, which can be classified into two groups based on EV charging demand assumptions: deterministic and uncertain (stochastic).

2.2.1 Deterministic Demand

The first group deals with locating stations under the assumption of deterministic refueling demand. Zheng et al. (2017) determined the optimal locations of EV charging stations to minimize the total system travel time and electricity consumption of travelers. Arslan and Karaşan (2016) developed a mixed-integer program for the EV charging station location problem, where the goal of the road infrastructure agency is to maximize the distance traveled by EVs. They solved the problem by using the Benders decomposition technique with Pareto-optimal cut implementations, which significantly reduced the computational time. He et al. (2018) proposed a bi-level framework for EV charging stations. The goal was to maximize the flow usage of the charging stations in the upper-level part. Anjos et al. (2020) focused on the interaction of EV adaption and the availability of charging stations over a long-term planning horizon. In this regard, they proposed a mixed-integer linear program model to determine the optimal construction of EV charging stations by maximizing the number of EVs in the network. They presented a rolling-horizon-based heuristic to solve the problem. Bai et al. (2019) studied the EV charging station location problem under the circumstances of a low EV penetration rate in the network. They used a vehicle's GPS dataset to identify some potential charging station locations. Based on the identified potential locations, the optimal charging station locations were determined through a bi-level framework that minimized the construction cost and maximized the electric charging service quality. To solve the presented bi-level framework, a hybrid algorithm combining non-dominated sorting genetic algorithm II (NGSA-II) and neighborhood search was applied. Kınay et al. (2021) studied both the optimal design of charging stations and the optimal routing of EVs. In this regard, two different problems were presented. The first sought to minimize the construction cost of charging stations and the total en-route recharging of EVs. The second model only minimized the total en-route charging of EVs. The authors applied a Bender decomposition algorithm to solve the problems. To support intercity trips for EVs, Fakhrmoosavi et al. (2021) studied the optimal charging station planning within the state of Michigan. The authors determined the optimal charging station configuration that minimized construction costs and travelers' delays. Khaksari et al. (2021) studied the optimal capacity planning of electric charging stations by proposing a mixed-integer program that minimized the construction cost of the charging stations. Moreover, their mixed-integer program ensured that the quality of the electric charging service for EVs, in terms of the probability of delay in charging complementation, was maintained above specific levels. Jordan et al. (2022)

incorporated real datasets of an urban area into a multi-objective optimization framework to select the best locations for electric charging stations. In this framework, they tried to maximize the utility coverage of the charging stations while minimizing their installation costs. Utility coverage was defined as the population, traffic, and activities covered by charging stations (Jordan et al., 2022). In another study, Xu et al. (2022) proposed a user-based location framework to maximize EV-user satisfaction with their charging experience (Xu et al., 2022). To improve the accuracy of demand prediction in long-term planning, Tungom et al. (2023) included a time-series linear regression in the EV charging station framework. The demand prediction stage helped to overcome the demand uncertainties in long-term planning. They proposed a hierarchical optimization approach to minimize the mismatch between demand-supply and investment costs while maximizing the quality of service for electric charging station users (Tungom et al., 2023).

2.2.2 Stochastic Demand

The second group of studies deals with uncertainty in both demand and supply (e.g., link capacity) of a traffic network. Sathaye and Kelley (2013) proposed a continuous optimization approach for constructing electric charging stations along highway corridors to minimize the distance traveled by EVs to recharge at charging stations, subject to a budget constraint. Hosseini and MirHassani (2015) developed a multi-period, two-stage decision framework to locate permanent and portable EV charging facilities. The portable facilities can be relocated across periods. In this framework, the road infrastructure agency determines the optimal locations of charging stations given the uncertainty in path flows on the traffic network. The present paper addresses the uncertainty of the recharging demand of travelers during their intercity trips and, therefore, can be placed in the second group of studies. Yıldız et al. (2019) studied the optimal configuration of electric charging stations that minimized the construction cost of electric charging stations, accounting for demand uncertainty in the optimal charging station planning and adopting a scenario-based approach to model such uncertainty. Kadri et al. (2020) proposed an optimization problem to maximize the expected served EV flows over a long-term planning horizon. The researchers incorporated the uncertainties about the electric recharging demand of EVs into the charging station planning and adopted a multi-stage stochastic integer programming approach based on a scenario tree to represent recharging demand uncertainty. Kchaou-Boujelben and Gicquel (2020) focused on driving range uncertainty in the optimal planning of electric charging stations. More specifically, they captured the uncertainties in the energy consumption of EVs and the energy availability of EV batteries. Liu et al. (2023) considered the uncertainties in electricity power output in bus electric charging station planning. They proposed a two-stage stochastic programming formulation that used a sample average approximation to capture the uncertainty of electricity power outputs. The proposed formulation tried to minimize different objectives like infrastructure investment, recharging costs, emissions costs, vehicle operation, and battery purchase. They discussed the tradeoff between objectives such as infrastructure investment and emission costs (Liu et al., 2023).

2.3 Wireless Electric Charging Lanes

Wireless electric charging lanes (WCL) enable EVs to charge their batteries while in motion. Wireless charging offers EVs a potentially unlimited driving range as long as the vehicle is operating in the charging lane. However, installing wireless electric charging lanes is challenging, as it is expensive and impacts traffic congestion. Therefore, a body of literature has focused on deploying optimal wireless electric charging lanes on road networks. In this subsection, some of the efforts that have been made to locate the wireless electric charging lanes are reviewed.

Chen et al. (2017) investigated the optimal deployment of charging stations and wireless charging lanes along a long traffic corridor to serve the electricity charging needs of EVs. They proposed a choice equilibrium model to capture the charging facility choices of EV drivers. Their model assumes EV drivers try to minimize their driving time, charging fees, charging time, and equipment costs (Z. Chen et al., 2017). Mubarak et al. (2021) proposed a framework for the optimal wireless charging lanes to serve the charging demand with minimum investment cost. Their proposed framework aimed to strategically deploy WCLs in the network in such a way that no EV runs out of energy before reaching its destination (Mubarak et al., 2021). In another study, Tran et al. (2022) integrated the dynamic routing behavior of travelers into the wireless charging lane location problem (Tran et al., 2022). Majhi et al. (2022) proposed a mixed-integer optimization model for the optimal placement of wireless charging lane facilities on a large road. The proposed model considered parameters that impact EV drivers' decision to charge their vehicles. They implemented the proposed model on a case study of the Auckland Highway using the data generated by a traffic simulation-based approach (Majhi et al., 2022). Du et al. (2022) proposed an optimization approach to determine the optimal locations and lengths of wireless electric charging lanes (Du et al., 2022). Odeh et al. (2022) presented an optimal allocation process for planning the locations of WCL lanes within the city of Dubai, UAE. They chose a set of candidate wireless electric charging lanes based on collected traffic data from the city. Then, they conducted an energy analysis on the selected candidate links to pick the most energy-efficient links to deploy wireless electric charging lanes (Odeh et al., 2022). He et al. (2023) presented a multiobjective optimization framework to deploy the optimal number of wireless charging lanes in a network. The presented framework aimed to maximize saved charging time, minimize charging costs, and minimize the negative impact of wireless charging lanes on traffic. Elghanam et al. (2023) proposed an integration of TOPSIS (technique for order of preference by similarity to ideal solution) and goal programming to determine the locations of wireless charging lanes. The proposed framework aimed to provide a comprehensive decision-making framework (Elghanam et al., 2023).

Table 2.1. Literature summary

	Study	Stochasticity	Planning horizon	Driving range heterogeneity	Refueling stations Decommissioning
Wireless charging	Chen et al. (2017)	Deterministic	Single	—	—
	Mubarak et al. (2021)	Deterministic	Single	—	—
	Tran et al. (2022)	Deterministic	Single	—	—
	Majhi et al. (2022)	Deterministic	Single	—	—
	Du et al. (2022)	Deterministic	Single	—	—
	Odeh et al. (2022)	Deterministic	Single	—	—
	He et al. (2023)	Deterministic	Single	—	—
	Elghanam et al. (2023)	Deterministic	Single	—	—
Charging station	Sathaye and Kelley (2013)	Stochastic (demand)	Multiple	—	—
	Hosseini and MirHassani (2015)	Stochastic (demand)	Multiple	—	—
	Karaşan (2016)	Deterministic	Single	—	—
	Zheng et al. (2017)	Deterministic	Single	—	—
	He et al. (2018)	Deterministic	Single	—	—
	Bai et al. (2019)	Deterministic	Single	—	—
	Yıldız et al. (2019)	Stochastic (demand)	Multiple	—	—
	Anjos et al. (2020)	Deterministic	Multiple	—	—
	Kadri et al. (2020)	Stochastic (demand)	Multiple	—	—
	Kchaou-Boujelben & Gicquel (2020)	Stochastic (driving range)	Single	Yes	—
	Kınay et al. (2021)	Deterministic	Single	—	—
	Fakhrmoosavi et al. (2021)	Deterministic	Single	—	—
	Khaksari et al. (2021)	Deterministic	Single	—	—
	Jordan et al. (2022)	Deterministic	Single	—	—
	Xu et al. (2022)	Deterministic	Single	—	—
	Tungom et al. (2023)	Deterministic	Multiple	—	—
	Liu et al. (2023)	Stochastic (electricity power output)	Single	—	—
	This study	Stochastic (demand)	Multiple	Yes	Yes

2.4 Summary

This chapter presents a review of the literature on electric charging facility planning. Table 2.1 shows a summary of the reviewed studies in this chapter. The majority of the studies assume deterministic values for the main planning components (e.g., travel demand and electricity consumption) and focus on a single-period planning horizon. However, there are a few studies that attempt to incorporate stochasticity in charging facility planning (Sathaye and Kelley, 2013; Hosseini and MirHassani, 2015; Yıldız et al., 2019; Kadri et al., 2020; Kchaou-Boujelben and Gicquel, 2020; Liu et al., 2023). Besides, none of the studies in the literature considered the heterogeneity of EV driving range (except Kchaou-Boujelben and Gicquel, 2020, which focused on the stochasticity of EV driving range) and refueling station decommissioning in long-term planning for electric charging stations. Therefore, this thesis aims to address these gaps and present a more holistic framework for electric charging station planning by developing a long-term planning framework incorporating demand uncertainties, heterogenous EV driving range, and the decommissioning of under-utilized refueling stations.

CHAPTER 3 METHODOLOGY

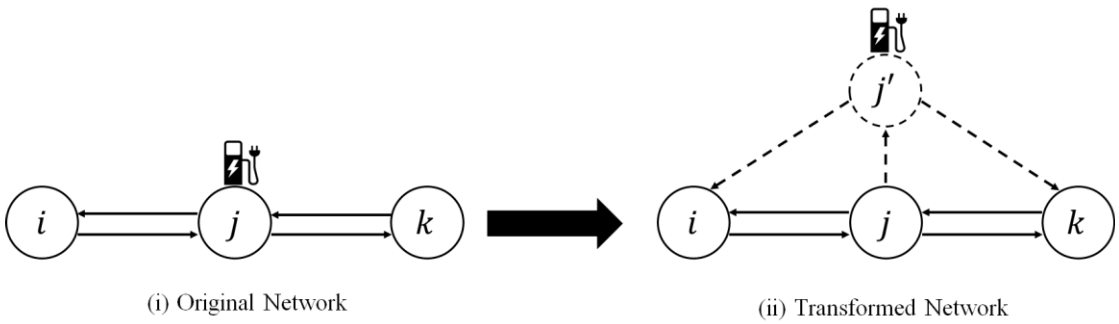
This chapter presents the methodology implemented in this thesis for a robust electric charging station deployment. First, the preliminary results of the proposed methodology are presented. Then, the proposed mathematical framework and the implemented solution algorithm are introduced.

3.1 Preliminaries

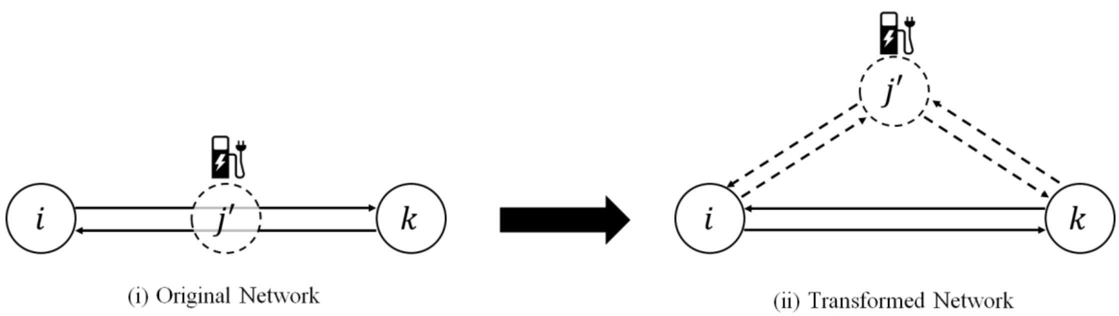
The presented methodology focuses on constructing level-3 charging stations on a rural road network. Hence, the effects of traffic congestion on travel time are neglected, and it is assumed that travelers experience free-flow travel time. Throughout this thesis, some other main assumptions are made. First, both ICEVs and EVs have limited driving range, and the driving range of ICEVs is higher than that of EVs. Next, ICEVs and EVs are fully refueled or recharged before departing from their origins. Travelers experience delays due to charging or refueling at corresponding stations. The refueling and charging stations have finite capacities and cannot serve more than their operational capacities. Also, travelers follow the user equilibrium (UE) principle in choosing their routes, minimizing their travel costs. Based on the increasing pattern of EV adaption, travel demand for EVs increases over the planning horizon. On the other hand, travel demand for ICEVs decreases.

Let $G = (N, A)$ represent the road network. The planning horizon is divided into T periods, which comprise the total duration of the planning horizon (typically, several years). Let τ denote the set of periods. The mixed-traffic scenario consists of EVs with different driving ranges and ICEVs. Let M denote the set of vehicle types with cardinality $|M|$ where class 1 denotes ICEVs. Let $m > 1$ denote different classes of EVs with different driving ranges, where $R^{m,t}$ is the driving range of EVs of class m in period t. The notations used in this study are introduced in the Notation section.

This study assumes that charging and refueling stations are located on nodes or links (specifically, beside the links). Travelers experience a delay during recharging or refueling. To capture the impact of charging and refueling delays on travelers and the operational capacity of stations, the road network configuration is modified. For each node or link with a charging or refueling station (either candidate or existing), a dummy node and certain dummy link(s) are included depending on the connection of the original node or link to other nodes in the road network. The set of dummy candidate nodes for charging stations is represented by $\bar{N}$. The set of dummy nodes with existing refueling and charging stations are denoted by $\bar{\bar{N}}$ and $\breve{N}$, respectively. $\breve{N}$ is assumed to be a subset of $\bar{N}$. Let $\check{A}$ denote the set of dummy links.



(a) electric charging station on a node



(b) electric charging station on a link

Figure 3.1. Transformation of traffic network

The network transformation is illustrated in Figure 3.1. Figure 3.1a represents the original network where the charging station is located on node j. To capture the impact of charging delay and the capacity of station j, dummy node j' is included in the charging station (Figure 3.1a). Since node j is connected to nodes i and k, two dummy links, (j',i) and (j',k), are included. The delay of the dummy link, (j, j'), $\hat{c}_{j,j'}^{m,t}$, is equal to the charging delay of EV travelers. The length of the dummy link is set to zero to ensure that it does not impact the driving range. Travelers who traverse through link (j, j') for recharging can continue their trips by using links (j', i), and (j', k) as they are identical to the links (j, i), and (j, k), respectively. Similarly, a dummy node j' is added to the network to capture the charging or refueling delay when a charging or refueling station is located at the link (Figure 3.1b). The dummy node j' is connected to nodes i and j by dummy links that have delays equal to the charge or refuel delays of EV and ICEV travelers, respectively. If travelers do not need to charge or refuel, they do not need to traverse through dummy links and use only the actual links of the network (links (i, k) or (k, i)). Besides, it is assumed that the refueling and charging stations serve travelers with finite operational capacities. The capacity of the newly constructed or existing charging stations is independent of the operational capacity of the refueling stations.

3.2 Mathematical Modeling

In practice, forecasts of travel demand are uncertain over a long-term planning horizon. This study assumes that it belongs to an uncertainty set. The travel demand uncertainty set for each vehicle class m for each O-D pair (r, s) in each period t is denoted by $Z_{r,s}^{m,t}$, in which $z = 1$ represents the deterministic travel demand scenario that can be used for analysis without considering travel demand uncertainty. It can denote the peak hour for travel demand. Let $\boldsymbol{p}$ denote the vector of the aforementioned binary variables, that is $\boldsymbol{p} = \{p_{r,s}^{m,z,t}, \forall(r, s) \in W, \forall m \in M, z \in Z_{r,s}^{m,t}, \forall t \in \tau\}$. For each vehicle class m traveling between O-D pair (r, s) in period t, there is only one realized travel demand scenario (therefore $\sum_{z\in Z_{r,s}^{m,t}} p_{r,s}^{m,z,t} = 1$). Given these notations, the travel demand uncertainty set Q can be formulated as follows:

$$Q = \{\boldsymbol{q} | \sum_{z\in Z_{r,s}^{m,t}} q_{r,s}^{m,z,t} p_{r,s}^{m,z,t} = q_{r,s}^{m,t}, \sum_{z\in Z_{r,s}^{m,t}} p_{r,s}^{m,z,t} = 1, p_{r,s}^{m,z,t} \in \{0,1\}\} \tag{1}$$

where $\boldsymbol{q} = (q_{r,s}^{m,z,t}, \forall(r, s) \in W, \forall m \in M, z \in Z_{r,s}^{m,t}, \forall t \in \tau)$ denotes the set of potential travel demand vectors. In deriving the optimal strategy for charging and refueling stations, if the road infrastructure agency does not account for travel demand uncertainty and instead only incorporates a certain vector of travel demand (such as peak-hour travel demand), then the robust scheme is reduced to a conventional "deterministic" scheme.

The proposed robust mathematical program involves multiobjective optimization; therefore, the weights of total system travel time (H_1) and the total penalty of unused charging station capacity (H_2) are denoted by ϕ_1 and ϕ_2, respectively. Ψ is defined as the penalty for unused charging station capacity. Let Δ^t be a factor for calculating the present value of costs in period t that reflects the interest rates through the long-term planning horizon. Then, Δ^t is equal to $\frac{1}{(1+\pi)^{t-1}}$. Let κ denote the parameter that converts the travelers' costs and unused charging station capacity from an hourly basis to the basis of each period duration (e.g., several days). The robust design of the charging network with refueling infrastructure can be formulated as the following min-max problem (MMP1):

<u>Upper-level model</u>

$$\min_{\boldsymbol{\varphi},\boldsymbol{\theta}}(\max_{\boldsymbol{p},\boldsymbol{v}} \, (\phi_1 \cdot \mathrm{H}_1 + \phi_2 \cdot \mathrm{H}_2)) \tag{2}$$

$$\mathrm{H}_1 = \sum_{t\in\tau} \Delta^t \cdot \kappa \cdot \beta^t \cdot (\sum_{(i,j)\in A} v_{i,j}^t \cdot c_{i,j}^t + \sum_{m\in M} \sum_{(i,j)\in\check{A}} v_{i,j}^t \cdot \hat{c}_{i,j}^{m,t}) \tag{3}$$

$$\mathrm{H}_2 = \sum_{t\in\tau} \Psi \cdot \Delta^t \cdot \kappa \cdot \sum_{j:(i,j)\in\check{A}|j\in\overline{N}} \sum_{i:(i,j)\in\check{A}} (n_j - v_{i,j}^t) \tag{4}$$

$$\varphi_i^1 = 1 \qquad \forall i \in \overline{\overline{N}} \tag{5}$$

$$\varphi_i^t \le \varphi_i^{t-1} \qquad \forall i \in \overline{\overline{N}}, \forall t \in \Gamma \tag{6}$$

$$\sum_{i\in\overline{N}} k_i^t \, \theta_i^1 \le B^1 \tag{7}$$

$$\sum_{i\in\overline{N}} k_i^t \, (\theta_i^t - \theta_i^{t-1}) \le B^t \qquad \forall t \in \Gamma, t > 1 \tag{8}$$

$$\theta_i^t = 1 \qquad \forall i \in \breve{N}, \forall t \in \Gamma \tag{9}$$

$$\theta_i^t \ge \theta_i^{t-1} \qquad \forall i \in \overline{N}, \forall t \in \Gamma \tag{10}$$

$$\bar{h}_j \cdot \varphi_j^t \le v_{i,j}^t \qquad \forall i \in N, \forall j \in \overline{\overline{N}}, \forall (i,j) \in \check{A}, \forall t \in \Gamma \tag{11}$$

$$v_{i,j}^t \le n_j \cdot \varphi_j^t \qquad \forall i \in N, \forall j \in \overline{\overline{N}}, \forall (i,j) \in \check{A}, \forall t \in \Gamma \tag{12}$$

$$v_{i,j}^{t} \leq n_j \cdot \theta_j^{t} \qquad \forall i \in N, \forall j \in \bar{N}, \forall (i,j) \in \check{A}, \forall t \in \Gamma \tag{13}$$

$$\theta_i^{t} \in \{0,1\} \qquad \forall i \in \bar{N}, \forall t \in \Gamma \tag{14}$$

$$\varphi_i^{t} \in \{0,1\} \qquad \forall i \in \bar{\bar{N}}, \forall t \in \Gamma \tag{15}$$

<u>Lower-level model</u>

$$f_{ij}^{w,t,1} \cdot \left(c_{ij}^{t} + \mu_i^{w,t,1} - \mu_j^{w,t,1}\right) = 0 \qquad \forall (i,j) \in A, \forall w, \forall t \tag{16}$$

$$c_{ij}^{t} + \mu_i^{w,t,1} - \mu_j^{w,t,1} \geq 0 \qquad \forall (i,j) \in A, \forall w, \forall t \tag{17}$$

$$f_{ij}^{w,t,m} \cdot \left(c_{ij}^{t} + \zeta_{ij}^{w,t,m} + \mu_i^{w,t,m} - \mu_j^{w,t,m}\right) = 0 \qquad \forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{18}$$

$$c_{ij}^{t} + \zeta_{ij}^{w,t,m} + \mu_i^{w,t,m} - \mu_j^{w,t,m} \geq 0 \qquad \forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{19}$$

$$f_{ij}^{w,t,m} \leq \Lambda\, e_{ij}^{w,t,m} \qquad \forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{20}$$

$$\zeta_{ij}^{w,t,m} \leq \Lambda\,(1 - e_{ij}^{w,t,m}) \qquad \forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{21}$$

$$\mu_s^{w,t,m} = 0 \qquad \forall w, \forall s, \forall t, \forall m \tag{22}$$

$$v_{i,j}^{t} = \sum_{w \in W} \sum_{m \in M} f_{ij}^{w,t,m} \qquad \forall t \tag{23}$$

$$\sum_{j:(j,i) \in A} f_{ji}^{w,t,m} - \sum_{j:(i,j) \in A} f_{ij}^{w,t,m} = q_i^{w,t,m} \qquad \forall w, \forall i, \forall t, \forall m \tag{24}$$

$$\zeta_{ij}^{w,t,m} \text{ and } f_{ij}^{w,t,m} \geq 0 \qquad \forall (i,j), \forall w, \forall t, \forall m \tag{25}$$

The goal of the presented model is to minimize the worst-case sum of system travel time (H_1) and the total penalty due to unused charging station capacity (H_2; Equation (2)). Equation (3) calculates the total travel delay of ICEV and EV travelers. Equation (4) calculates the total unused electric charging stations and refueling stations. Constraints (5) ensure that refueling stations exist in the first period and can be used by ICEVs. Constraints (6) state that if the refueling station of node i stops working in period $t-1$, then it cannot be patronized by ICEVs for the rest of the planning horizon. Constraints (7) and (8) ensure that the monetary budget for the construction of the new charging stations is satisfied in each period. Constraints (9) state that the existing charging stations are available for charging throughout the entire planning horizon. Constraints (10) ensure that once a charging station is constructed in a period, it remains available for charging in subsequent periods. Constraints (11) ensure that the refueling station of node j works in period t if its demand is greater than or equal to $\bar{h}_j$. Constraints (12) are the capacity constraints of refueling stations, which state that the number of vehicles that refuel at node j in period t (i.e., traverse through the dummy link (i,j)) is less than n_j if the refueling station is available in that period. It also ensures that after removing the refueling station at node j, the refueling demand at that node becomes zero. Constraints (13) are identical to constraints (12) except that they apply to the charging stations, meaning that the number of vehicles that recharge at node j in period t is less than n_j if the charging station located at node j is available for charging in period t, and 0 otherwise. Constraints (14)–(15) state that θ_i^t and φ_i^t are binary variables.

The second body of the model ((16)–(25)) addresses the route choice behavior of travelers. Constraints (16)–(17) are the UE conditions for ICEV users, which ensure that if ICEV users of each O-D pair use link (i,j), it belongs to the path between that O-D pair with minimum travel cost. Similarly, constraints (18)–(19) are the UE conditions for EV users. Constraint (20) ensures that if link (i,j) does not belong to the feasible path between an O-D pair, the flow of EVs is zero. Similarly, constraint (21) imposes an excessive travel cost on a link (i,j) that is not a part of the feasible EV path. Constraint (22) indicates that travel time at the origin is equal to zero. Equation (23) calculates the total traffic flow of link (i,j) in period t. Constraint (24) ensures demand conservation, and constraint (25) ensures the non-negativity of $\zeta_{ij}^{w,t,m}$ and $f_{ij}^{w,t,m}$.

An important component of the above formulation ((2)–(25)) is the feasible path of EVs ($e_{ij}^{w,m,t}$). Considering the heterogeneous driving range of ICEVs and EVs, the feasible paths of EVs ($e_{ij}^{w,m,t}$) are derived as a set of mixed-integer linear programs (equations (26)–(39)).

$$u_j^{w,m,t} \geq {u'}_i^{w,m,t} + L_{ij} - \Lambda\left(1 - e_{ij}^{w,m,t}\right) \qquad \forall (i,j) \in A, \forall w, \forall m, \forall t, \forall i, j \tag{26}$$

$$u_j^{w,m,t} \leq {u'}_i^{w,m,t} + L_{ij} + \Lambda\left(1 - e_{ij}^{w,m,t}\right) \qquad \forall (i,j) \in A, \forall w, \forall m, \forall t, \forall i, j \tag{27}$$

$$u_i^{w,m,t} \leq R^{m,t} \qquad \forall t, \forall w, \forall m, \forall i \tag{28}$$

$$u'^{w,m,t}_{i} \geq u^{w,m,t}_{i} - \Lambda\, \theta^{t}_{i} \qquad \forall t, \forall w, \forall m > 1, \forall i \in N - (\breve{N} \cup \bar{\bar{N}}) \qquad (29)$$

$$u'^{w,m,t}_{i} \leq u^{w,m,t}_{i} + \Lambda\, \theta^{t}_{i} \qquad \forall t, \forall w, \forall m > 1, \forall i \in N - (\breve{N} \cup \bar{\bar{N}}) \qquad (30)$$

$$u'^{w,m,t}_{i} \leq \Lambda\, (1 - \theta^{t}_{i}) \qquad \forall t, \forall w, \forall m > 1, \forall i \in \bar{N} \qquad (31)$$

$$u'^{w,m,t}_{i} = 0 \qquad \forall i \in \breve{N}, \forall m > 1, \forall t, \forall w \qquad (32)$$

$$u'^{w,m,t}_{i} \leq \Lambda\, (1 - \varphi^{t}_{j}) \qquad \forall i \in \bar{\bar{N}}, \forall m = 1, \forall t, \forall w \qquad (33)$$

$$u'^{w,m,t}_{s} = 0 \qquad \forall s | (s, r) \in W, \forall m, \forall t, \forall w \qquad (34)$$

$$u^{w,m,t}_{s} = 0 \qquad \forall s | (s, r) \in W, \forall m, \forall t, \forall w \qquad (35)$$

$$\sum_{w, m>1, j:(j,i)\in A} f^{w,t,m}_{ji} \leq \bar{n}_j\, \theta^{t}_{i} \qquad \forall t, \forall i \in \bar{N} \cup \breve{N} \qquad (36)$$

$$\sum_{j,w} f^{w,t,1}_{ji} \leq \bar{\bar{n}}_i \varphi^{t}_{i} \qquad \forall t, \forall i \in \bar{\bar{N}} \qquad (37)$$

$$u'^{w,t}_{i}, u^{w,t}_{i}, g^{w,t,m}_{i}, h^{t}_{i} \geq 0 \qquad \forall t, \forall w, \forall i \qquad (38)$$

$$e^{w,t,m}_{ij} \in \{0,1\} \qquad \forall t, \forall w, \forall (i, j) \in A \qquad (39)$$

Constraints (26) and (27) calculate the distance that travelers traveled from the last-visited refueling stations (for $m = 1$) or charging station (for $m > 1$) after visiting node j and just before visiting node i. Constraints (28) ensure that the traveled distance of vehicles ($u^{w,m,t}_{j}$) is less than the driving range in period t ($R^{m,t}$). Constraints (29) and (30) ensure that if a charging station is not located at node i, the traveled distances from the last-visited charging station just before visiting node i ($u^{w,t}_{i}$) and after visiting node i ($u'^{w,t}_{i}$) are equal. If a charging station is constructed at node i, then $u'^{w,t}_{i}$ is equal to zero (constraints (31)). This implies that the traveled distance is set to zero after visiting the constructed charging stations. Similarly, if there is a charging station at candidate node i, then $u'^{w,t}_{i}$ is equal to zero (constraint (32)). Similarly, if a charging station operates at node i, then ${u'}_i^{w,t}$ is equal to zero (constraint (33)). Constraints (34) and (35) ensure that ($u_i^{w,t}$) and (${u'}_i^{w,t}$) are zero at the origin of the trips. Constraint (36) calculates the total volume of EVs that recharge at station i and ensures that this not exceed the capacity of that charging station. Constraint (37) ensures that the served ICEVs do not exceed the capacity of the refueling stations. Especially, it ensures that when a refueling station is decommissioned, it does not serve ICEVs anymore. Constraint (38) ensures the non-negativity of ${u'}_i^{w,t}, u_i^{w,t}, g_i^{w,t,m}$, and h_i^t. Finally, $e_{ij}^{w,t,m}$ is a binary variable set according to constraint (39).

3.3 Solution Algorithm

The proposed MMP1 (equations (2)–(39)) contains two types of binary variables and is classified as a mixed-integer problem. It cannot be solved in polynomial time and, therefore, is described as non-deterministic polynomial hard (NP-hard). Many solution algorithms are used to solve NO-hard problems in the literature (Miralinaghi, et al., 2017a; Miralinaghi, et al., 2017b; Pourgholamali et al., 2023; Labi et al., 2023; Seilabi et al., 2022a; Seilabi et al., 2022b). This study uses the cutting-plane scheme to solve MMP1 (2)–(39) by addressing two subproblems during each iteration (Lou et al., 2009; Seilabi et al., 2023). The first subproblem determines the optimal timeline for locating new charging stations and decommissioning the existing refueling stations (equations (1)–(39)) based on a subset of the travel demand uncertainty set. The second subproblem generates a new worst-case travel demand scenario. To implement this scheme, first, MMP1 should be formulated as the following mixed-integer problem (MMP2):

$$L_2 = \min_{\boldsymbol{\varphi},\boldsymbol{\theta}}(\omega) \tag{40}$$

$$\begin{aligned}\omega \geq \phi_1 \cdot \sum_{t\in\tau} \Delta^t \cdot \beta^t \cdot \kappa \cdot \left(\sum_{(i,j)\in A} v_{i,j}^{t,q} \cdot c_{i,j}^t + \sum_{m\in M} \sum_{(i,j)\in \breve{A}} v_{i,j}^{t,q} \cdot \hat{c}_{i,j}^t \right) + \\ \phi_2 \cdot \sum_{t\in\tau} \Delta^t \cdot \Psi \cdot \kappa \cdot \left(\sum_{j:(i,j)\in\breve{A}|j\in\bar{N}} \sum_{i:(i,j)\in\breve{A}} (n_j - v_{i,j}^{t,q}) \right) \qquad \forall q \in Q\end{aligned} \tag{41}$$

$$v^q \in \Omega(\boldsymbol{q}) \qquad \forall q \in Q \tag{42}$$

where the superscript $(\cdot)^q$ denotes the variables that are associated with a specific travel demand uncertainty vector $q \in Q$. Although the number of feasible scenarios for the travel demand of each vehicle class m of O-D pair (r, s) in period t is particularly small, the number of vectors in the travel demand uncertainty set (Q) is generally very large. In MMP2, equations (11)–(39), which present the UE conditions, need to be written for each $q \in Q$. To prevent presenting repetitive equations, equation (42) represents the equations (11)–(39) for each $q \in Q$. Therefore, $\Omega(\boldsymbol{q})$ represents the UE link flows for each $q \in Q$. Due to the tremendous increase in the number of constraints, the relaxed MMP2 is solved using a subset $\tilde{Q} \subseteq Q$ that includes a restricted number of travel demand vectors. The idea of the cutting-plane scheme is to update the subset $\tilde{Q}$ unless it is not possible to identify a travel demand vector that leads to a higher weighted summation of total travel cost and penalties of unused charging station capacity compared to the current solution (i.e., the worst-case travel demand scenario). Given the operating refueling and electric charging stations, the following mixed-integer problem (MMP3) updates the subset $\tilde{Q}$

$$\max_{\boldsymbol{p}} \left(\phi_1 \cdot \mathrm{H}_1 + \phi_2 \cdot \mathrm{H}_2 \right) \tag{43}$$

$$\sum_{z \in Z_{r,s}^{m,t}} p_{r,s}^{m,z,t} = 1 \tag{44}$$

$$p_{r,s}^{m,z,t} \in \{0,1\} \tag{45}$$

and equations (3), (4), (11)–(13), (16)–(39).

Based on the developed subproblems, a solution algorithm consists of eight main steps. To begin, the feasible paths of ICEVs and EVs are found based on the available refueling and charging stations (Step 1). The feasible paths are used to capture the route choice of travelers. In Step 2, the uncertain travel demand set is initialized by selecting a travel demand set (or vector). In this step, the nominal travel demand is selected and added to the uncertain travel demand set. Next, an optimal plan for constructing new charging stations and decommissioning refueling stations is obtained by solving the MMP2 (Step 3). Based on the new optimal plan, the feasible routes for travelers are updated (Step 4). Then, MMP3 is solved to update the uncertain travel demand set (Step 5). In the next step, the termination condition is checked. Two termination conditions are considered in this study: the total number of iterations and not finding any further worst-case travel demand scenarios. If the conditions are met, the process stops and returns the latest optimal plan

(Step 8). If not, it goes to Step 7 and adds the solution of MMP3 to the worst-case travel demand scenario. Figure 3.2 presents a simplified flowchart of the implemented solution algorithm.

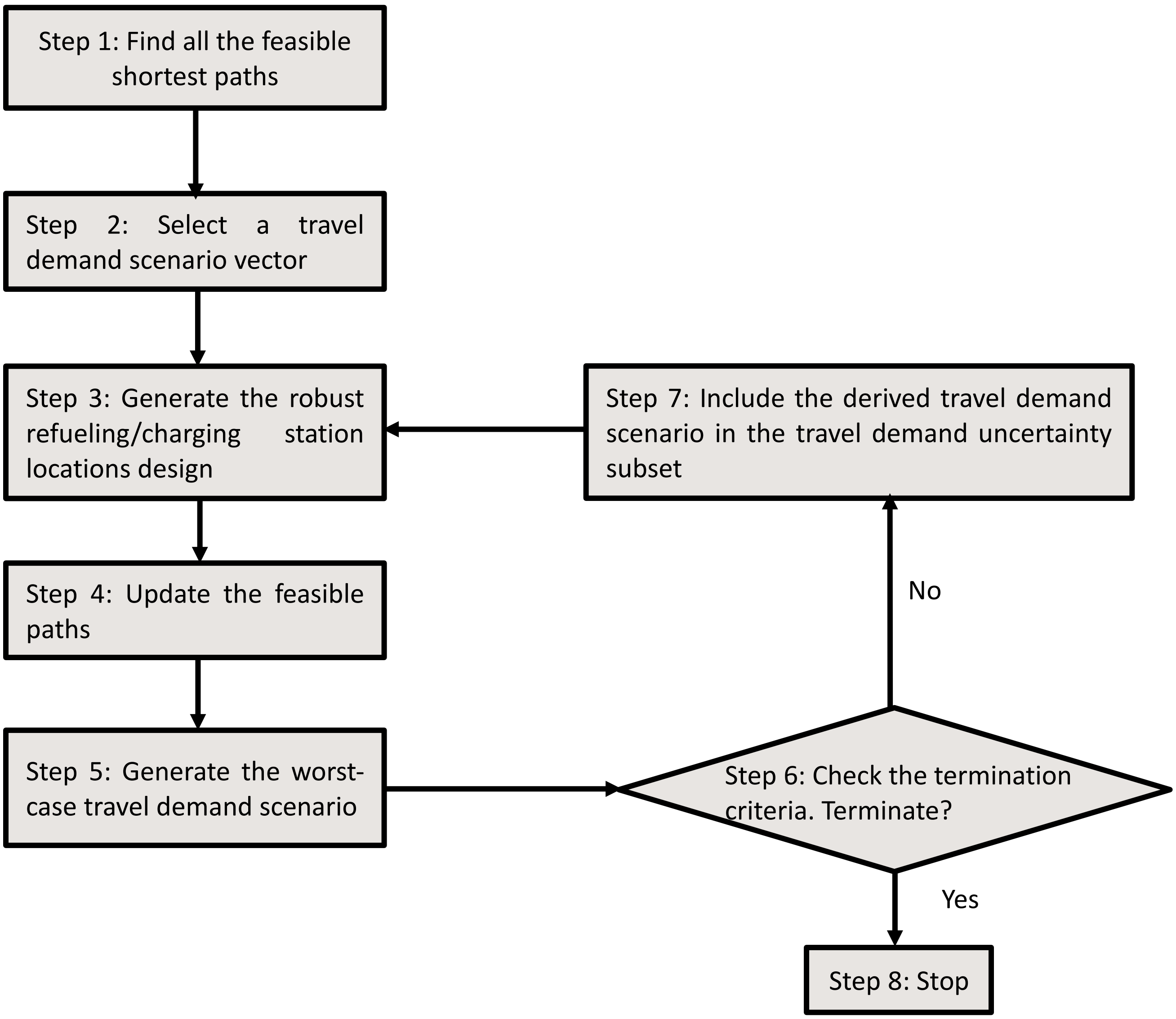


Figure 3.2. Flowchart of the implemented solution algorithm

CHAPTER 4 NUMERICAL EXPERIMENTS

4.1 Case Study

This section presents the results of numerical experiments using the well-known Sioux Falls city road network (Figure 4.1), which has 24 nodes and 76 links. The road agency seeks the optimal timeline for constructing new EV charging stations and decommissioning existing refueling stations over the planning horizon.

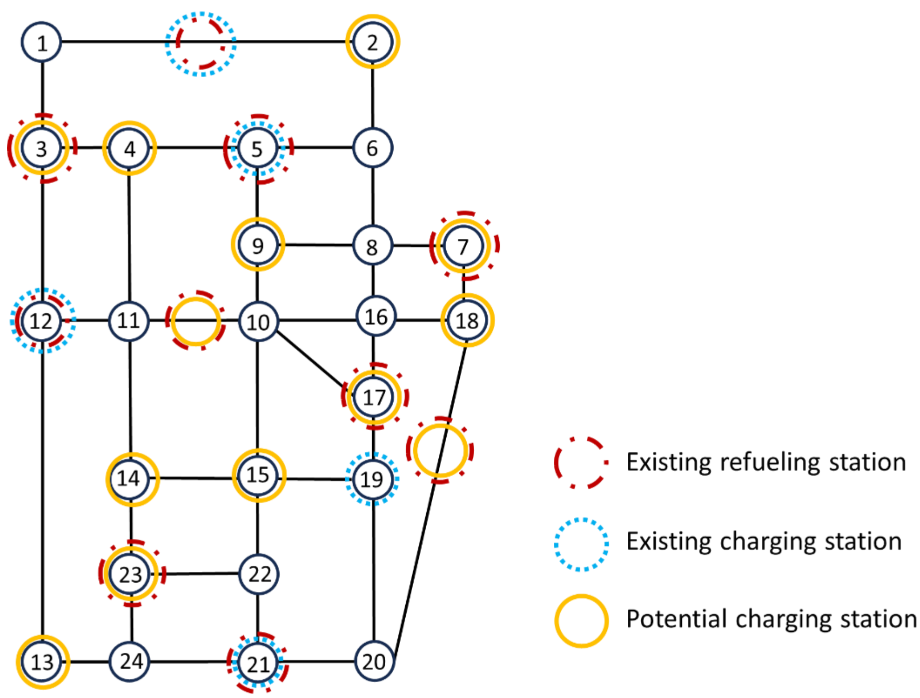


Figure 4.1. Sioux Falls network of refueling and charging stations

The horizon is assumed to be equal to 18 years, with 6 time periods of 3-year duration each. The characteristics of this network have been modified to better mimic intercity travel compared to the characteristics proposed by LeBlanc et al. (1975). The link characteristics (travel times and lengths) and the aggregate peak-hour travel demand of each origin-destination (O-D) pair in period 1 are listed in Table 4.1 and Figure 4.2, respectively.

Origin Zone		Destination Zone																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
	1	0	3	6	18	9	12	15	24	18	42	18	9	18	9	15	18	15	6	9	9	3	12	9	6
	2	3	0	3	9	3	15	6	15	9	18	6	6	9	3	6	12	9	3	3	6	3	6	3	3
	3	6	3	0	9	3	9	3	6	6	9	9	9	6	3	3	6	3	0	3	3	3	3	3	3
	4	18	9	9	0	15	15	15	21	24	36	45	21	18	15	15	24	15	3	9	12	6	12	15	9
	5	9	3	3	15	0	9	6	18	24	30	18	6	6	6	9	18	9		6	6	3	6	6	3
	6	12	15	9	15	9	0	12	24	12	24	12	9	9	6	9	30	18	3	9	12	3	9	6	3
	7	15	6	3	15	6	12	0	33	18	57	15	24	15	9	15	42	30	6	15	18	9	18	6	3
	8	24	15	6	21	18	24	33	0	27	48	27	18	18	12	21	66	42	9	21	27	12	18	12	6
	9	18	9	6	24	24	12	18	27	0	84	45	21	18	18	30	45	30	6	15	21	12	21	18	6
	10	42	18	9	36	30	24	57	48	84	0	120	63	57	66	120	132	117	21	54	78	39	81	54	27
	11	18	6	9	45	18	12	15	27	45	120	0	45	30	48	45	42	30	6	15	21	15	33	42	18
	12	9	6	9	21	6	9	24	18	21	63	45	0	42	21	24	21	21	6	9	15	12	24	21	15
	13	18	9	6	18	6	9	15	18	18	57	30	42	0	18	21	21	18	3	12	21	18	39	24	24
	14	9	3	3	15	6	6	9	12	18	66	48	21	18	0	39	21	21	3	12	15	12	36	33	12
	15	15	6	3	15	9	9	15	21	30	120	45	24	21	39	0	39	45	9	24	33	24	78	30	15
	16	18	12	6	24	18	30	42	66	45	132	42	21	21	21	39	0	84	15	42	51	18	36	18	9
	17	15	9	3	15	9	18	30	42	30	117	30	21	18	21	45	84	0	21	51	51	21	51	18	9
	18	6	3		3	3	3	6	9	6	21	6	6	3	3	9	15	21	0	12	15	3	12	3	3
	19	9	3	3	9	6	9	15	21	15	54	15	9	12	12	24	42	51	12	0	39	15	39	12	6
	20	9	6	3	12	6	12	18	27	21	78	21	15	21	15	33	51	51	15	39	0	39	75	21	15
	21	3	3	3	6	3	3	9	12	12	39	15	12	18	12	24	18	21	3	15	39	0	57	21	18
	22	12	6	3	12	6	9	18	18	21	81	33	24	39	36	78	36	51	12	39	75	57	0	66	36
	23	9	3	3	15	6	6	6	12	18	54	42	21	24	33	30	18	18	3	12	21	21	66	0	24
	24	6	3	3	9	3	3	3	6	6	27	18	15	24	12	15	9	9	3	6	15	18	36	24	0

Figure 4.2. Aggregate travel demand for each origin-destination (O-D) pair in period 1

4.2 Problem Setting

The travel demand uncertainty set for O-D pair w and vehicle class m in time period t consists of four demand sets: (1) travel demand scenario at peak hour, (2) low travel demand scenario, (3) medium travel demand scenario, and (4) high travel demand scenario. Travel demand scenarios 2 to 4 are derived by multiplying travel demand scenario 1, as the benchmark, with random parameters that are generated based on the uniform distribution. The domain of the low travel demand scenario is [0.95, 1] in period 1, while the lower bound decreases consistently during the transition horizon until it reaches [0.7, 1] in period 6. The domains of medium and high travel demand scenarios are [1, 1.05] and [1, 1.1] in period 1, respectively, while the upper bounds increase during the transition horizon until they reach [1, 1.3] and [1, 1.6] for the medium and high travel demand scenarios, respectively. The value of time (β^t) is assumed to be equal to $20/hour in the first period (U.S. Department of Transportation, 2016). It is assumed that this value increases by $2 in each period and reaches $30/hour in period 6. The aggregate travel demand for each O-D pair is assumed to grow by 5% in each period. There are two classes of EVs with different driving ranges: 150 and 200 miles in period 1 for EV types 1 and 2, respectively. These ranges increase in each period to reach 200 and 250 miles in period 6 for EV types 1 and 2, respectively (Mazda USA, 2022; Nissan USA, 2022; Volvo Cars, 2022). The driving range of ICEVs is considered to be equal to 250 miles for all periods. The EV class market penetration starts at 2.5% of aggregate travel demand of each O-D pair in the first period and increases constantly until reaching 40% in period 6. On the other hand, the market penetration of ICEV vehicles starts at 95% and decreases to 20% in the last period. The proposed algorithm (Figure 3.2) was coded in the general algebraic modeling system (GAMS) using CPLEX solver. The results were obtained using a Core i7 processor with a 2.6 GHz CPU and 8 GB RAM.

Table 4.1. Link characteristics of Sioux Falls network

Link No.	From	To	Travel Time (min)	Length (mile)	Link No.	From	To	Travel Time (min)	Length (mile)
1	1	2	60.34	71.52	39	13	24	37.67	44.64
2	1	3	43.94	52.08	40	14	11	44.75	53.04
3	2	1	60.34	71.52	41	14	15	45.77	54.24
4	2	6	52.35	62.04	42	14	23	43.03	51.00
5	3	1	43.94	52.08	43	15	10	59.43	70.44
6	3	4	43.64	51.72	44	15	14	45.77	54.24
7	3	12	41.92	49.68	45	15	19	35.44	42.00
8	4	3	43.64	51.72	46	15	22	35.44	42.00
9	4	5	21.87	25.92	47	16	8	48.80	57.84
10	4	11	65.41	77.52	48	16	10	45.56	54.00
11	5	4	21.87	25.92	49	16	17	16.91	20.04
12	5	6	42.22	50.04	50	16	18	27.24	32.28
13	5	9	50.93	60.36	51	17	10	81.41	96.48
14	6	2	52.35	62.04	52	17	16	16.91	20.04
15	6	5	42.22	50.04	53	17	19	23.39	27.72
16	6	8	21.97	26.04	54	18	7	22.07	26.16
17	7	8	25.31	30.00	55	18	16	27.24	32.28
18	7	18	22.07	26.16	56	18	20	45.16	53.52
19	8	6	21.97	26.04	57	19	15	35.44	42.00
20	8	7	25.31	30.00	58	19	17	23.39	27.72
21	8	9	97.30	115.32	59	19	20	40.40	47.88
22	8	16	48.80	57.84	60	20	18	45.16	53.52
23	9	5	50.93	60.36	61	20	19	40.40	47.88
24	9	8	97.30	115.32	62	20	21	57.92	68.64
25	9	10	27.84	33.00	63	20	22	47.69	56.52
26	10	9	27.84	33.00	64	21	20	57.92	68.64
27	10	11	50.62	60.00	65	21	22	16.91	20.04
28	10	15	59.43	70.44	66	21	24	33.31	39.48
29	10	16	45.56	54.00	67	22	15	35.44	42.00
30	10	17	81.41	96.48	68	22	20	47.69	56.52
31	11	4	65.41	77.52	69	22	21	16.91	20.04
32	11	10	50.62	60.00	70	22	23	40.50	48.00
33	11	12	65.41	77.52	71	23	14	43.03	51.00
34	11	14	44.75	53.04	72	23	22	40.50	48.00
35	12	3	41.92	49.68	73	23	24	19.04	22.56
36	12	11	65.41	77.52	74	24	13	37.67	44.64
37	12	13	30.17	35.76	75	24	21	33.31	39.48
38	13	12	30.17	35.76	76	24	23	19.04	22.56

It is assumed that the network has 10 existing refueling stations located at nodes 3, 5, 7, 12, 17, 21, and 23 and at links (1,2), (10,11), and (18,20). There are also 5 existing charging stations at nodes 5, 12, 19, and 21 and at link (1,2). Figure 4.1 illustrates 13 candidate locations for constructing new charging stations, which are nodes 2, 3, 4, 7, 9, 13, 14, 15, 17, 18, and 23 and links (10,11) and (18,20). The construction costs of new charging stations are assumed to be identical for all candidate locations. This cost starts at $0.5 million in the first period, increases by $0.1 million in each period, and reaches $1 million in the sixth period. The construction budget for new charging stations in each period is equal to $1.5 million in periods 1 to 4 and equal to $1 million for periods 5 and 6. The charging delay is assumed to be equal to 30 minutes in the first period for EVs (i.e., $m > 1$) as the approximation for the delay of the current fast-charging stations (Mazda USA, 2022; Nissan USA, 2022; Volvo Cars, 2022). The charging delay is assumed to decrease during the planning horizon due to technological advancements and reach 10 minutes in period 6. For ICEVs (i.e., $m = 1$), the refueling delay is assumed to be constant and equal to 5 minutes during the planning horizon. The operational capacities (n_j) of charging and refueling stations are 60 and 150 vehicles per hour, respectively. The penalty for the unused charging station capacity is assumed to be equal to $10 per hour.

In this case study, equal weights for the two considered objective criteria in the objective function (i.e., $\phi_1 = \phi_2 = 1$) are assumed. The constant interest rate (π) for each period during the entire planning horizon is assumed to be equal to 5 percent. Hence, Δ^t is equal to $\frac{1}{1.05^{t-1}}$. Furthermore, κ equals 26,280 (that is, $24 \times 365 \times 3$) to convert the hourly-based costs to the basis of each period duration (i.e., 3 years). The conversion factor presents the system costs in a way that is more representative of real-world applications, and its value does not affect the analysis outcomes. For implementation, this factor could be adjusted to fit and represent the real-world conditions associated with those applications. Finally, it is assumed that up to five shortest paths can be utilized for each O-D pair and vehicle class in each period ($k = 5$). In the rest of this chapter, the performance of robust planning is investigated. To do this, the robust scheme and the deterministic scheme are compared (Section 4.3). Then, the impacts of the available budget for constructing charging stations on the robust framework are discussed (Section 4.4).

4.3 Comparison of the Robust and Deterministic Schemes

In this section, the performance of robust planning is investigated. To do this, the optimal long-term plan of the proposed robust framework, which is called the "robust scheme," is compared to its counterpart, the "deterministic scheme." The deterministic scheme is the optimal long-term plan of the proposed framework, except the only deterministic values of demand are assumed to be travel demand (therefore, the travel demand uncertainty set contains only one travel demand set, which is the deterministic travel demand).

First, the obtained locations and decommissioning timelines under deterministic and robust schemes are compared. Figure 4.3 shows the optimal location of constructed charging stations and decommissioned refueling stations. Under the robust scheme, there are three additional charging stations compared to the deterministic scheme during the planning horizon. This is due to the higher conservatism of the road agencies, who consider the worst-case travel demand scenario in the optimal design, in robust scheme. Under the robust scheme, charging stations are constructed in the most congested areas of the network (nodes 7, 9, and 18) with higher demands expected for this area in the first period. With the exception of node 7, this result stands in contrast to the result from the deterministic scheme, which proposes to build the charging stations in the less congested areas of the region and on the borders of the network (nodes 2 and 13).

Furthermore, both schemes suggest almost identical designs for decommissioning the existing refueling stations, except for period 5 (Table 4.2). Both schemes suggest decommissioning refueling stations located at node 23, link (10,11), node 3, and node 17 in periods 2, 3, 4, and 6. Under the deterministic scheme, the refueling station on node 12 must be decommissioned in period 5, while the robust scheme suggests decommissioning the refueling station located at link (18,20) in period 5. This similarity is due to the fact that the total operational capacity of refueling stations is significantly higher than the refueling demand, and considering the worst cases of travel demand vectors in the robust scheme compared to the deterministic scheme, does not make a significant difference in the list of existing refueling stations to be decommissioned under either scheme.

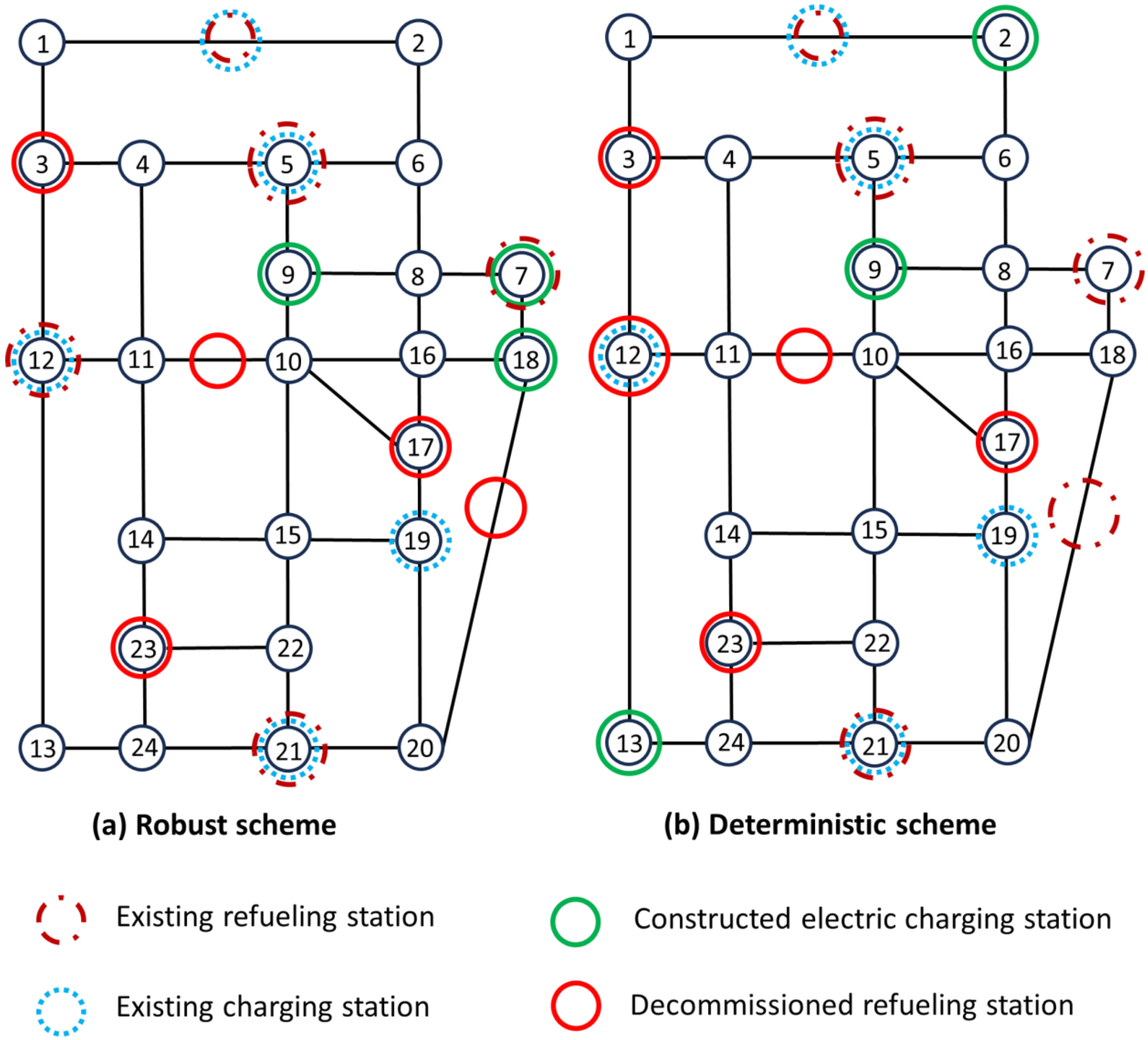


Figure 4.3. Optimal locations of constructed charging and decommissioned refueling stations

Table 4.2. Optimal decommissioning plan

(a) Robust scheme

Refueling station	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
Node 23		X				
Link (10,11)			X			
Node 3				X		
Link (18,20)					X	
Node 17						X

(b) Deterministic scheme

Refueling station	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
Node 23		X				
Link (10,11)			X			
Node 3				X		
Node 12					X	
Node 17						X

Next, the performance of the deterministic and robust schemes under uncertainty in the long-term travel demand forecasts is investigated. To do this, three Monte Carlo simulations are implemented. In these analyses, 1,000 travel demand vectors for each simulation are generated based on the different distributions that use travel demand scenarios (1)–(4). The distributions for simulations 1 to 3 include (1) optimistically asymmetric distribution with higher occurrence probability (that is, 0.4) for low and peak-hour travel demand scenarios and lower occurrence probabilities for medium (0.15) and high (0.05) travel demand scenarios; (2) discrete uniform distribution with identical occurrence probability for each travel demand scenario (that is, 0.25); and (3) pessimistically asymmetric distribution with higher occurrence probability (that is, 0.4) for medium and high travel demand scenarios and lower occurrence probability for peak-hour (that is, 0.15) and low (that is, 0.05) travel demand scenarios.

The relative performances of the robust and deterministic schemes in each of the three simulations are compared based on the three measures: (i) travelers' costs, (ii) charging costs of

EVs, and (iii) standard deviation of travelers' costs (). "Travelers' costs" refers to the monetized travel time experienced by travelers. The induced delay for EV travelers due to charging their EVs at charging stations is called the "charging cost of EVs." Overall, travelers' costs increase from simulation 1 to simulation 3 under both robust and deterministic schemes. This is due to the increase in travel demand from simulation 1 to simulation 3. Under simulations 1–3, the robust scheme reduces average travelers' costs compared to the deterministic scheme. More specifically, the robust scheme outperforms the deterministic scheme in terms of average travelers' cost by 25, 18, and 43 million dollars over the course of 18 years of planning horizon in simulations 1 to 3, respectively. The reason the robust scheme outperforms the deterministic scheme is that many travel demand sets (instead of only one set) are considered in developing a robust scheme.

Additionally, the standard deviation of the travelers' cost under a robust scheme is also less than or equal to that under the deterministic scheme in simulations 1–3, which demonstrates the less volatile performance of the robust scheme compared to the deterministic scheme. This is due to the more conservative approach of the road infrastructure agency under the robust scheme to plan for the worst-case travel demand scenario. A similar discussion applies to the differences between robust and deterministic schemes in terms of the average total cost and the charging cost of EVs.

Table 4.3. Performance of the robust and deterministic schemes in the Monte Carlo simulation

Simulation	Measures (in million dollars)	Robust Scheme	Deterministic Scheme
1	Average travelers' cost	$70,760	$70,803
	Average charging cost of EVs	$5,115	$5,159
	Standard deviation of travelers' cost	101	102
2	Average travelers' cost	$75,135	$75,160
	Average charging cost of EVs	$5,474	$5,498
	Standard deviation of travelers' cost	145	146
3	Average travelers' cost	$78,821	$78,839
	Average charging cost of EVs	$5,776	$5,795
	Standard deviation of travelers cost	119	120

Sim1 tends to have relatively lower demand levels on average

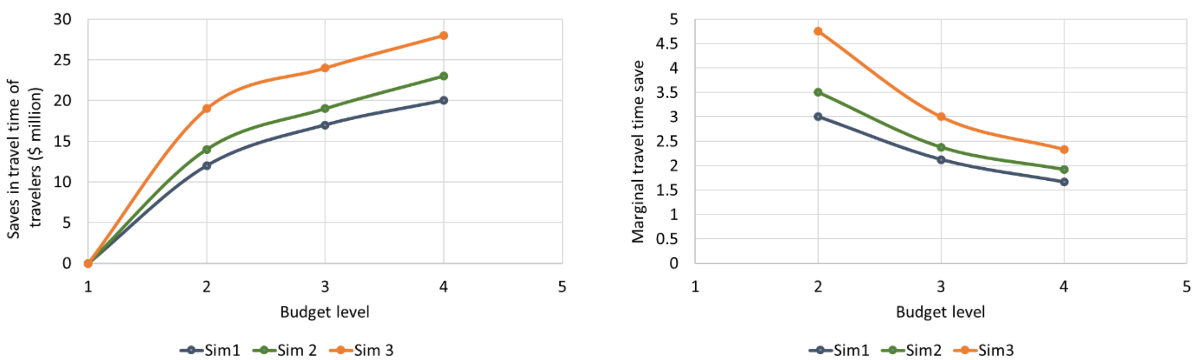
Sim2 tends to have relatively medium demand levels on average

Sim3 tends to have relatively higher demand levels on average

Details of simulations are provided on pages 52 and 53.

4.4 Impacts of Construction Budget

Next, the impacts of the construction budget on the optimal design of electric charging infrastructure are investigated using four cases. The construction budget used in the previous analysis (Section 4.3) is referred to as case 1, which is a base case in this analysis. The construction budget in each period for cases 2 to 4 is derived by multiplying the construction budget of case 1 by 1.5, 2, and 2.5 for each period, respectively. Therefore, the corresponding budgets for cases 2–4 are as follows: 12, 16, and 20 million dollars, respectively. In the analyses of this section, budget case 1 is considered the base case, and the performance of other cases is compared to budget case 1. Figure 4.4 shows the effects of a budget increase on the travel time savings of travelers. Travel cost savings refers to the difference between the monetized total travel time of a budget case and budget case 1. Increasing the construction budget saves more travel time for travelers due to more constructed charging stations and their accessibility (Figure 4.4a). Therefore, increasing the construction budget results in more charging stations and a reduction in travel time for travelers. However, the marginal savings of travel time (savings in travel time per construction budget) decreases by increasing the budget (Figure 4.4b). This shows that even though more charging stations are constructed in cases 3 and 4 compared to case 2, this does not result in a significant decrease in the average travelers' cost. Because there are enough charging stations on the network, constructing more charging stations cannot help travelers further decrease their travel costs.

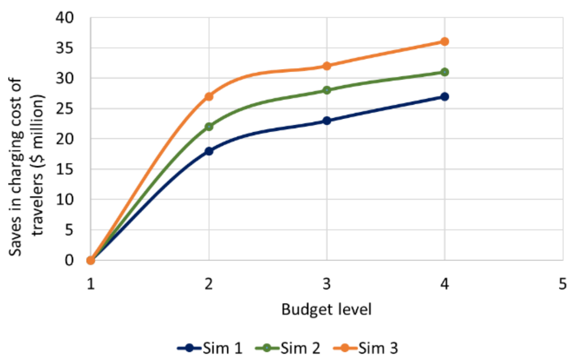


(a) Savings in total travel time

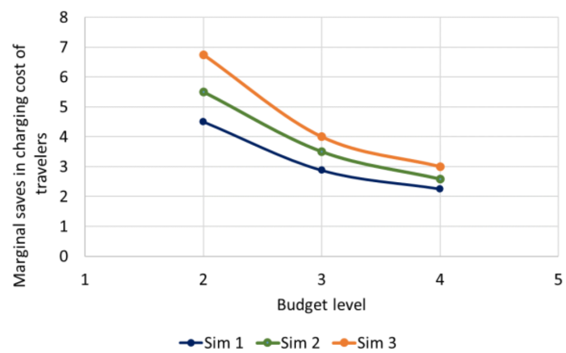
(b) Marginal travel time savings

Figure 4.4. Effects of budget on travel time and travelers' cost

Besides the savings in total travel time of travelers, the effects of construction budgets on the total savings in charging costs of EVs are investigated (Figure 4.5). The effects of the construction budget on the total charging costs of EVs are similar to the discussed effects on the total travel cost of travelers. Similarly, Figure 4.5a shows that increasing the construction budget increases the saved charging costs of EVs (defined as the difference between the charging costs of EVs in a budget case and budget case 1). Moreover, the marginal saved charging costs show decreasing patterns over the budget costs (Figure 4.5b).



(a) Total savings in charging cost



(b) Marginal savings in charging cost

Figure 4.5. Effects of budget on charging cost of EVs

Next, the effects of the construction budget on the unused charging station capacity are discussed. As expected, increasing the construction budget results in more charging stations in the network and, therefore, more unused charging station capacity (Figure 4.6). Although there is a penalty for the unused capacity, the number of constructed charging stations increases with the increase in the budget. This is because the decrease in travelers' costs caused by constructing more charging stations prevails over the penalties caused by the unused charging station capacity. For instance, in simulation 1, the travelers’ cost decreases by $14 million in case 2, while the penalty for unused charging station capacity is increased by $0.16 million.

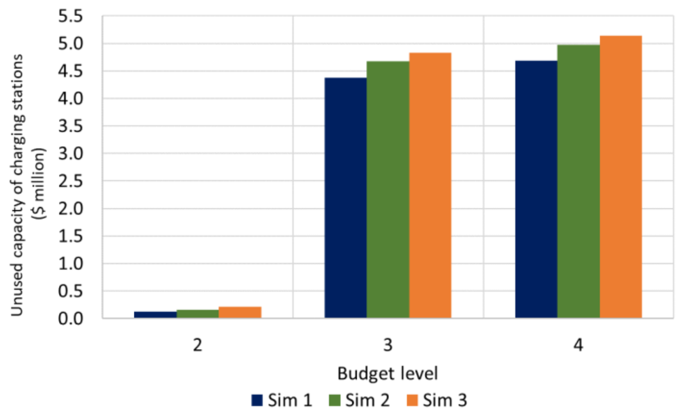


Figure 4.6. Effects of budget on unused electric charging capacity

The comparison of robust schemes under different budget cases is summarized in Table 4.4. Besides the total travel time and charging costs of EVs, the actual expenditures under the budget cases are shown in Table 4.4. Under budget cases 2 and 3, the construction expenditure increases by $3 million compared to case 1 due to the higher number of charging stations constructed. However, it decreases by $1 million under budget case 4 compared to cases 2 and 3, since more charging stations are constructed in the initial periods with lower costs. As the construction budget increases, there is more construction in the initial periods of the planning horizon since the construction is less costly in those periods compared to the latter ones.

Table 4.4. Relative performance of the robust schemes with different construction budget levels

Sim #	Measures (in million dollars)	Construction Budget Case		
		2	3	4
1	Relative construction expenditure	+$3	+$3	+$2
	Relative travelers' cost	–$12	–$17	–$20
	Relative penalty of unused charging station capacity	+$0.12	+$4.38	+$4.68
	Relative charging cost of EVs	–$18	–$23	–$27
2	Relative construction expenditure	+$3	+$3	+$2
	Relative travelers' cost	–$14	–$19	–$23
	Relative penalty of unused charging station capacity	+$0.16	+$4.67	+$4.97
	Relative charging cost of EVs	–$22	–$28	–$31
3	Relative construction expenditure	+$3	+$3	+$2
	Relative travelers' cost	–$19	–$24	–$28
	Relative penalty of unused capacity of charging stations	+$0.21	+$4.83	+$5.14
	Relative charging cost of EVs	–$27	–$32	–$36

Sim1 tends to have relatively lower demand levels on average;
Sim2 tends to have relatively medium demand levels on average
Sim3 tends to have relatively higher demand levels on average

Details of simulations are provided on pages 52 and 53.

CHAPTER 5 CONCLUDING REMARKS

5.1 Study Conclusion

This study investigated the optimal location of electric charging stations and the decommissioning of existing refueling stations in the context of intercity trips over a long-term planning horizon. The uncertainties in refueling and electric charging demand are taken into account by considering uncertainties in travel demand forecasts over a long-term planning horizon. Then, the research accounts for uncertainty in travel demand forecasts using a travel demand uncertainty set for each period. Furthermore, due to the significant difference in driving ranges of various EV models, this study also accounts for the driving range heterogeneity of EVs.

The problem is formulated as a min-max mathematical program where the weighted sum of the worst-case (maximum) total system travel cost and the total penalty for unused charging station capacity during the planning horizon is minimized. The formulated min-max problem is considered an NP-hard problem; therefore, a cutting-plane scheme is adopted to solve the problem efficiently, where two subproblems are solved in each iteration. The first subproblem yields the optimal timeline and location for constructing new charging stations and decommissioning existing refueling stations based on a subset of demand uncertainty sets. The second subproblem identifies a new worst-case travel demand uncertainty vector to include in the demand uncertainty subset of the first subproblem.

The problem is applied to the Sioux Falls network. It is assumed that for this network, the road infrastructure agency seeks to determine the optimal location and timeline for constructing new electric charging stations and decommissioning existing refueling stations. It is shown that, due to the higher conservatism of the road infrastructure agency under the robust scheme, a higher number of charging stations needs to be constructed compared to the deterministic scheme. Further, under the robust scheme, new charging stations are located in more congested areas of the network compared to the deterministic scheme. It is also observed that if the refueling demand is significantly lower than the operational capacity of refueling stations, there is no significant difference between the robust and deterministic scheme strategies for decommissioning existing refueling stations.

Three sets of Monte Carlo simulations were carried out to assess the performance of a robust scheme compared to its deterministic counterpart. The results of the computational experiments illustrate that the proposed robust scheme outperforms the deterministic scheme based on various criteria such as travelers' costs, charging cost of EVs, construction cost, and total cost. In particular, while the deterministic scheme cannot satisfy any of the simulation instances generated based on the uniform and pessimistically asymmetric distributions, all the simulation instances are feasible under the proposed robust scheme. Further, the comparison of robust schemes with different classes of construction budgets illustrates that although constructing more charging stations helps to decrease travelers' costs, constructing too many charging stations beyond a certain point does not significantly decrease travelers' costs.

The framework presented for constructing electric charging stations over a long-term planning horizon can provide guidance to road agencies in their long-term planning and budgeting functions. This is important in the current era where these agencies continue to seek knowledge on how they can best prepare the existing roadway infrastructure to support a new era of transformative transportation technologies, including automated, connected, and electric vehicles. Such guidance can also help mitigate the inherent uncertainties associated with long-term planning with regard to these technologies. The level of service is always a function of supply and demand, and as stewards of the public road infrastructure, road agencies are responsible for anticipating demand and providing infrastructure supply. On the one hand, inadequate infrastructure will not only slow the adoption of new technologies but also pose public relations problems for the agency. On the other hand, excess supply will lead to capacity underutilization, economic inefficiency, and the waste of scarce resources. The developed framework can also help road agencies prepare proactively for emerging technologies in a more confident manner. Additionally, the framework can be used by agencies to incorporate robustness into their long-term EV infrastructure plans to account for the inevitable uncertainties associated with supply and demand. The framework presents (and demonstrates), for the benefit of road agencies, the advantage of robust planning over deterministic planning. Further, the framework is designed to be flexible to adjust to the road agency's future objectives, which often evolve with changes in the political environment, economic conditions, or social forces. The framework and solution method are designed to facilitate the practical implementation of various network topologies, inventories of existing or required charging and refueling stations, and lengths of planning horizons.

5.2 Study Limitations and Future Work

This research can be extended in several directions. First, although our study considers the uncertainty in travel demand, there are other sources of uncertainty that should be considered in electric charging station planning, especially in long-term planning. For example, the uncertainty in the market penetration of different classes of EVs has not been assessed. An interesting research direction would be to investigate the market penetration rate of EVs as a stochastic function of charging station availability, electricity or gas prices, and potential government incentives. Another important source of uncertainty is the adequacy of electric power at the charging stations. Electric charging stations may experience fluctuations in the available electricity supplied by the electric grid. Therefore, considering uncertainties in the electric charging station capacity in the planning framework is another direction for future studies. Second, this study does not incorporate any updated information on travel demand into the planning framework. However, as time goes on, updated predictions, which are mostly more accurate than the initial predictions, will become available and can be used in the planning framework. Therefore, an adaptive framework is needed to include updated information on travel demand in the planning framework.

Third, the emergence of connected and autonomous vehicles (CAVs), which are expected to serve as EVs, could impose high levels of uncertainty on the charging behavior of EV-using travelers. Hence, another future research direction is to incorporate the charging behavior of CAVs into the robust design of charging stations. Seilabi et al. (2022c) and Pourgholamali et al. (2023) discussed the sibling relationships including the synergies between CAVs and EVs. Fourth, this thesis assumes fast-charging stations are the only electric charging types in the network. However, wireless electric charging lanes and dynamic electric charging (Konstantinou and Gkritza, 2021) are the other expected electric charging methods that could be used by intercity travelers. Therefore, incorporating the other electric charging methods is another direction for future studies.

Other prospective directions for future research on EV charging infrastructure investment planning include consideration of emissions (McLaren et al., 2016; Miralinaghi et al., 2020), which can be further reduced with enhanced planning that promotes EV market growth and ICEV market decline; alternative charging fee revenue impacts from EV charging fee policies and associated revenues (Konstantinou et al., 2022); regional-scale location planning of EV charging stations (Chen et al., 2023); and the synergies associated with car sharing and ride sharing (Liao and Correia, 2022).

In addition, the present study focuses on intercity trips; the link travel times are assumed to be constant, and thus, prospective future studies could address intracity trips and duly consider urban traffic congestion. Finally, this study did not consider the time EV users spend waiting at charging stations when there is no available charging spot, and it assumed that EV users simply pass that charging station and drive to another one. However, EV users may wait at charging stations until a charging spot becomes available instead of driving to another charging station.

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