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Facilitating electric-propulsion of autonomous vehicles through efficient design of a charging-facility network

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Facilitating Electric Propulsion of Autonomous Vehicles Through Efficient Design of a Charging-Facility Network

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16. Abstract
Electric vehicles, autonomous or manual, provide a valuable opportunity to address issues of environmental pollution, climate change, and national security. In recognition of the synergies between vehicle electrification and autonomy, this study addresses the facilitation of vehicle electrification in the prospective future era where autonomous vehicles become mainstream. Part 1 of this study proposes a methodology for scheduling deployment of electric charging facilities (charging guideways and charging stations) at AV dedicated lanes over candidate links of a road network over a long-term horizon period. The methodology is intended to assist highway agencies in decision support regarding the scheduling, locations, and operating capacities of the EV charging facilities, where the road users (travelers) minimize their travel times by selecting routes and their preferred vehicle type (AV vs. HDV). The bi-level model is solved using a Genetic Algorithm, and the results provide insights into the impacts of alternative scenarios of charging infrastructure investment. Part 2 of the study presents a methodology for environmentally sustainable electric charging station deployment, such that travelers experience a smooth shift from ICEVs to EVs over a lengthy planning horizon. This involves gradually decommissioning existing gas stations and commissioning of new EV charging stations at those locations, and greenfield deployment of new charging stations at new locations to meet energy demand. At the upper level of the bi-level optimization framework, the agency (decision-maker) minimizes systemwide vehicle emissions. At the lower level, travelers minimize their travel times by choosing route and vehicle types in response to the upper-level decisions. The results of Part 2's numerical experiments emphasize the importance of EV charging station availability and adequate driving range in EV market promotion. The results suggest the extent to which deployment budget size and driving range enhancement can increase EV market penetration and consequently, reduce vehicle emissions. Part 3 discusses the potential benefits, opportunities, costs, and challenges of vehicle electrification. Part 4 presents a summary of the report, highlights of the findings, and concluding remarks. Part 4 also presents the USDOT performance indicators in the context of this study, and the study's research outputs, broad outcomes, and impacts.

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LIST OF ACRONYMS

AC	Alternating Current
AEV	Autonomous Electric Vehicle
AFV	Alternative-fuel Vehicle
AV	Autonomous Vehicle
AV	Autonomous Vehicle
BEV	Battery Electric Vehicle
BPR	Bureau of Public Roads
CACC	Cooperative Adaptive Cruise Control
CAV	Connected and Autonomous Vehicle
CO	Carbon Monoxide
CSP	Constrained Shortest Path
DC	Direct Current
EAV	Electric Autonomous Vehicles
EV	Electric Vehicle
HDV	Human-Driven Vehicle
GA	Genetic Algorithm
GHG	Greenhous Gas
HDV	Human-driven Vehicle
IOO	Independent Owner and/or Operator
ICEV	Internal Combustion Engine Vehicle
IDM	Intelligent Driver Manual
MINLP	Mixed-Integer Nonlinear Problem
MPEC	Mathematical Program with Equilibrium Constraint
NCP	Nonlinear Complementarity Problem
NP-Hard	Nondeterministic Polynomial-time Hard Problem
NSGA-II	Non-dominated Sorting Genetic Algorithm II
O-D	Origin-Destination
PHEV	Plug-in Hybrid Vehicle
PO	Pareto Optimal
UE	User Equilibrium
VOT	Value of Time

LIST OF COMMONLY USED TERMS

Transportation decision-maker — This is the road agency that owns the roadway infrastructure. This agency is responsible for construction of both road lane types (general purpose and AV) and both EV charging facilities (guideways and stations). Often, a private-sector entity develops the EV-only or EV- charging lane or charging stations. The entity may own or operate this infrastructure independently. In such cases, the transportation decision maker is the road agency that makes or promotes such investments in conjunction with the private-sector entity.

Electric charging facility — This is the infrastructure or device that provides electrical recharge to the vehicle. This could be:

- charging stations (where both the charger and the vehicle are stationary);
- charging guideways (where the charger [guideway or pavement] is stationary and the vehicle can be mobile); and
- portable chargers (where the charger vehicle provides charging at a fixed location or in motion to the vehicle).

This report addresses only the first two types.

EV charging facility planning — Involves long-term decisions on EV charging infrastructure, regarding their locations, year of installation/construction, and charging capacity.

Traffic network user equilibrium — Users of a congested road network that seek to make decisions regarding the trip route associated with minimal travel cost from the origin to the respective destination, and choose such path selfishly. At equilibrium, the number of trips between an origin and a destination equals the travel demand associated with the market price (i.e., the trip travel times), and all users with identical origin and destination have identical travel time.

Lane management — Sharing of the roadway cross section carriageway among the different vehicle types. A lane may be dedicated (to EAV only or HDV only), or general purpose (both EAV and HDV). General purpose lanes are also referred to as mixed lanes or missed-use lanes.

Bi-level model — A nested model where a “leader” makes decisions at one level (upper level) and the followers at another level (lower level) react by making decisions optimal from their perspective. In making a decision that optimizes its objective, the leader anticipates the optimal response of the followers. Derived from Stackelberg’s hierarchical leader-follower game theory concept.

AV-EV synergy	Implicit cooperation and interaction of automation and electric propulsion to yield a combined impact that is superior to the sum of their individual impacts.
Dynamic charging	Charging an EV while it is in motion.
Charging station	Stationary equipment that connects an electric power source to an EV using a connector cable, to recharge the EV.
Charging rate	Range extension (travel distance or travel time) added to the EV battery per unit distance or per unit time, respectively.
Charging station capacity	Number of electric vehicles that can be charged simultaneously at a given EV charging station.
Tradeoff	The exchange of something of value, particularly as part of a compromise.
Lane type	Purpose of a lane regarding a specific use, for example, general-purpose lane and EV-exclusive lane. In some literature, defined as "Lane class."
General-purpose lane	Regular lane for all users irrespective of propulsion energy source (EVs and internal combustion engine vehicles (ICEVs).
EV-exclusive lane	Dedicated lane for EV users only.
EV driving range	Estimated distance that can be driven by an EV given a certain level of battery charge.
EV charging facility method	Relative motion between the charging source and the EV. Static vs. dynamic.
Static charging	Charging a parked EV.
Wireless charging lane	Equipment that recharges an EV without a connector (cable). May be statis or dynamic.
EV Market penetration	The rate at which EVs are being purchased and/or patronized by travelers, as a fraction of all vehicles in the overall traffic fleet at a given time, within a given jurisdiction.

CHAPTER 1 GENERAL INTRODUCTION

Vehicle automation can yield overall transportation cost savings to individuals and thereby enhance market penetration of AVs particularly where they are electric (Offer, 2015). Other researchers have argued that the explicit and targeted integration of vehicle automation and electric propulsion is unavoidable because of the ease and convenience of powering a non-human-driven vehicle with electricity instead of gasoline. It is anticipated that vehicle automation combined with vehicle electrification will help make travel more efficient and productive. AVs are expected to be cost-effective to travelers at cities, where trips are of short duration and are made within the city, vehicle occupancy is typically high, and EV charging stations are generally relatively more accessible (Freedman et al., 2018). It has been recognized that the sibling technologies of vehicle automation and electrification, combined with connectivity and shared ownership, will converge, thereby collectively and holistically disrupting the transportation landscape (Adler et al. (2019)). Ha et al. (2021) suggested that (a) the benefits of the sum of these technologies is potentially superior to the sum of their individual benefits, and (b) the holistic benefits of any two or more of these technologies may likely be more achievable when the technologies are at a mature stage rather than at a nascent stage.

Regarding transportation electrification, there remains a clear and urgent need for this technology which promises to help control emissions from mobile sources. GHG emissions are a main cause of climate change (IPCC, (2007), Metz et al., (2007). This continues to be of great interest to transportation planners and engineers because the transportation sector remains the second largest GHG emissions source globally (Aziz et al., 2017) due to the dominance of the internal combustion engine (ICE) and its fossil fuel use. Transportation not only consumes 49 percent of fossil fuels and produces 27 percent of total GHG emissions worldwide but also is the sector with the fastest-growing energy consumption worldwide (EPA, 2015). Efforts to cut GHG emissions globally were intensified after the 2017 Paris Agreement which was signed by 195 countries. Despite international promotion efforts, EVs currently face several adoption barriers including higher purchase price, low driving range (distance that can be travelled by a fully charged vehicle before it will need replenishment) and relative scarcity of charging infrastructure compared to ICEVs' refueling stations. As of 2022, there were only 53,000 public electric charging stations in the U.S. which is significantly low compared to the number existing gas stations (145,000) (World Economic Forum, 2022). Consumer expectations of alternative-fuel vehicle range are rather high (Fuller, 2016); current BEV batteries can generally provide 100-400 miles (USDOE, 2021). Automakers and policymakers are currently exploring methods to overcome the first two barriers. For example, under California's clean vehicle rebate project, that state's Environmental Protection Agency (CalEPA) rebates ZEV purchases by up to $5,000. This study focuses on the third barrier mentioned: scarcity of charging infrastructure.

The advent of autonomous vehicles provides an opportunity to reduce transportation related GHG emissions indirectly (Kopelias et al., 2020). First, the AV's connectivity technology allows platooning with low headways, thereby increasing road capacity, improving traffic throughput, and reducing emissions. Second, AVs are expected to be electrically propelled, and it is expected that AVs will gain a foothold in the market at a time when the EV market penetration is high. Recent studies have suggested that electric vehicle owners are interested in purchasing AVs (Lam et al., 2018). In view of environmental benefits of EVs, government and non-governmental agencies have shown great interest in the transition from ICEVs to EVs. Also, automakers, spurred by government policy and regulation, are making specific efforts to increase the EV market share in order to realize these benefits. For example, the United Kingdom and France are planning to end sales of ICEV by 2040 (Racherla and Waight, 2018). Also, Volvo had announced in 2017 that its ICEV production line would end in a few years as subsequent vehicles produced will all be electric (Vaughan, 2017). Apart from these efforts, most automakers and some high-tech companies have recently attempted to put forward real-world applications by combining AV technology with EVs. For example, all Tesla vehicles now come equipped with full AV hardware and electric engines (The Tesla Team, 2016). It has been reported that carsharing and ridesharing companies intend to use EAVs in their fleets because AV technology is important to improving service quality and lowering operating costs (Yi and Shirk, 2018).

Generally, the EV adoption rate has lagged expectation and the market share remains miniscule. For example, in the United States, the current market share of EVs is less than 2% (Smith et al., 2019). As mentioned earlier in this chapter, EVs currently face a number of adoption barriers, including those related to charging time, range anxiety (distance covered by a fully charged vehicle), and insufficient availability of charging facilities compared to ICEVs gasoline stations (Ashkrof et al., 2020). The availability and efficiency of EV charging facility technologies are crucial to EV market penetration. It is expected that research related to EV charging facility planning and design can help resolve these barriers. Three modes of EV charging are discussed in the literature (Adler and Mirchandani, 2014; Kettles, 2015):

- Static or station charging involves charging an EV parked at the station via cable.
- Guideway or dynamic charging: an in-pavement or continuous roadside charger charges the battery as the vehicle moves on the roadway.
- Battery swapping, where a depleted battery is replaced by a fully charged one at a battery-swapping station.

Static or station charging is the most common charging method. This can be further classified into three levels based on the recharge equipment power level. At the first level, the EV is charged using a standard residential 120-volt AC outlet. As of the time of reporting, this takes about 20 hours to recharge a fully spent battery. The second level uses 220-volt residential or 208-volt commercial AC electrical service, which requires at least 7 hours of recharge. The third level, DC fast charging, uses a commercial grade 480-volt AC power service with at least 20 minutes recharge time (Kettles, 2015). **Guideway or dynamic charging** helps to increase the driving range and reduces the EV charging time. Also, guideway charging reduces the required level of battery power and significantly reduces the EV initial cost (Ko and Jang, 2013). In addition, due to the reduced battery weight, the EV propulsion power increases. Wireless-charging facilities can yield benefits in terms of simplicity, reliability, and ease-of-use compared to static charging, and the efficient and reliable charging they provide can encourage patronage of EVs. However, a wireless charging facility is costly to construct, maintain, and operate and has problems of electromagnetic compatibility, limited transfer of power, and lower efficiency due to the air-gap distance between the source and receiver (Moon et al., 2014). In addition, wireless-charging lanes could attract traffic and thereby end up as congested spots in the network. The presence of charging lanes can reduce the original road capacity by 8%–17% because of the different driving manner in wireless-charging lanes (He et al., 2018). Such driving differences could be minimized if the vehicles are AVs. **Battery swapping** stations require significant space for storing the swapping supplies, equipment, and for the swapping operations. Swapping is facilitated when the battery is standardized and easily replaceable.

In this report, the term "transportation decision maker" is used copiously. This refers to the public-sector or private-sector independent owner or operator (IOO) that owns and/or operates the roadway or charging infrastructure. The IOO is responsible for construction of both road lane types (general purpose and EV/AV) and one or both EV charging facilities (guideways and stations). In some cases, the private-sector IOO develops the dedicated lane and/or charging facility through a lease, design-build-operate contract for the public roadway, or as infrastructure owned or operated independently of the main road network. In such cases, the transportation decision maker is the public sector IOO (often, a road agency) that makes the EV charging facility location decisions in conjunction with the private sector IOO.

The first part of this report addresses the fundamental planning problem of optimally locating electric charging facilities (guideways and/or stations) at candidate links of a road network having general-purpose lanes and AV-dedicated lanes. The study proposes a methodology for scheduling these deployments over a long-term horizon period. The methodology is associated with the agency's objective of minimizing overall travel time subject to a budget constraint, and the travelers' objective of minimizing their travel times by selecting routes and their preferred vehicle type (AV vs. HDV). Therefore, this part of the study seeks to provide a framework that road agencies can use to identify optimal locations of static and/or dynamic charging stations at their road networks and to investigate the impacts of alternative scenarios of charging infrastructure investment.

The second part of the report considering travel demand develops and demonstrates an environmentally sustainable EV deployment framework such that travelers experience a smooth shift from ICEVs to EVs over a long planning horizon. Recent literature suggests that such horizon could span at least 2 decades in France and UK (Racherla and Waight, 2018). The goal is to gradually transition the existing gasoline stations to electric charging stations and to deploy new charging stations at new locations as and where needed, to meet travel energy demand. Doing this will promote EVs and will help achieve the goal of zero emissions in the next few decades. During the HDV-CAV transition phase, it is anticipated that there will exist multi-use stations, that is, stations that have gasoline refueling pumps and electric charging facilities and therefore can serve both ICEVs and EVs. A gradual and smooth gasoline-electric transition is important because any abrupt decommissioning of gasoline stations will render ICEVs to be unable to refuel. On the other hand, if the IOO provides the charging stations at a rate that is far less commensurate compared to the EV adoption rate, then EV users will not have sufficient access to charging stations, and this will discourage travelers from purchasing EVs. Therefore, any EV network charging framework must: (i) meet the charging needs of an increasing number of EV consumers and (ii) address the refueling needs of ICEV customers in the long term. Also, this framework should be capable of accounting for the influence of EV charging infrastructure availability on EV market penetration over the analysis horizon.

The third part of the report address the implementation issues, challenges, and opportunities regarding charging infrastructure for autonomous vehicles, and the fourth part presents the overall concluding remarks from the study, a synopsis of the USDOT performance indicators, and the outcomes, outputs, and impacts of this study, and the list of references.

Part I

CHAPTER 2 INTRODUCTION TO PART I

2.1 Background and motivation

2.1.1 The problem of emissions

The widespread use of fossil fuels (mainly, coal and petroleum) to meet energy requirements negatively impacts climate and the environment and leads to widespread consequences including greenhouse gas (GHG) emissions. Such emissions constitute a significant threat as they accelerate climate change (Metz et al., 2007). At the 21st conference of the parties held in Paris in 2015 (Paris Agreement), the 195 participating countries declared their intention to minimize greenhouse gas emissions (UNFCCC, 2019). The EU-28 and its member states have stated that they are committed to reducing at least 40% of GHG emissions by 2030 compared to 1990 levels (European Union, 2014).

Due to the dominant use of internal combustion engine vehicles (ICEVs), the transportation sector remains the largest contributor of any sector, to GHG emissions (Sinha & Labi, 2007; EPA, 2015). This sector, which consumes 49 percent of fossil fuels and produces 27 percent of total GHG emissions worldwide, is the sector with the fastest-growing energy consumption worldwide (Riba et al., 2016; IEA, 2017; Ghosh, 2020).

2.1.2 The promise of AVs and AV-exclusive lanes

AVs are more likely to be EVs not ICEVs, and therefore will help reduce emissions. Secondly, the connectivity feature of AVs provides a valuable opportunity to reduce transportation-related GHG emissions (Kopelias et al., 2020; Bauer et al., 2015; Xu et al., 2020) because the connectivity technology of AVs facilitates platooning with reduced headways. This increases road capacity, improves traffic mobility (Ha et al., 2020) and reduces emissions. Tientrakool et al. (2011) showed that with full adoption of connected AVs, the road capacity could be tripled and yet, with low AV market penetration, the system-level travel impacts are small. They argued that this problem could be addressed by implementing AV-exclusive lanes.

2.1.3 The EV aspect of EAVs

In recognition of the AV-EV synergy, it has been suggested that AVs will be introduced into the market when the EV market share is high (Lam et al., 2018). Furthermore, according to recent studies, electric vehicle (EV) consumers are also interested in purchasing AVs (Berliner et al., 2019; Hardman et al., 2019). As a result, future AVs are most likely to be electric (Lam et al., 2018). EAVs will not emit GHG at source, and therefore could represent a promising solution to help reduce climate change and environmental pollution (Jochem et al., 2015; Liang et al., 2016). In view of these environmental benefits of EVs, government and non-governmental agencies are greatly interested in the transition from ICEVs to EVs (ECE, 2015). Also, automakers, spurred by government policy and regulation, are making specific efforts to increase the EV market share in order to realize these benefits. For example, UK and France are planning to end sales of ICEV by 2040 (Racherla & Waight, 2018). Also, Volvo announced in 2017 that its ICEV production line would end soon and that all vehicles produced thereafter will be electric (Vaughan, 2017).

However, despite these efforts, the adoption rate of EVs has lagged behind expectation, and the EV market share remains miniscule. For example, in the United States, the EV current market share is less than 2% (Chen et al., 2020; Smith et al., 2019). In 2017, very few countries, such as Sweden (3.8%) and Belgium (2.1%), had an EV market share of more than 2% (The World Database on Sales of Electric Vehicles, 2017). The Netherlands' (3.87%) EV market share in 2014 fell to 1.5% in 2017 (IEA, 2017). EVs currently face a number of adoption barriers, including those related to charging time, range anxiety (distance covered by a fully-charged vehicle), and insufficient availability of charging facilities compared to ICEVs' gasoline stations (Ashkrof et al., 2020; Biresselioglu et al., 2018).

2.1.4 EAV charging and the alternatives.

Charging performance is crucial to EV market penetration. Therefore, research into EV charging facility planning can help resolve some of the barriers to EV market share. A good balance between investment and use should be achieved in improving the EV charging facilities: as stated earlier in this chapter, if too few facilities are provided, this will cause delay and range anxiety for EV users. On the other hand, excessive EV charging facilities will lead to capacity underutilization and energy supply inefficiency. IOOs are responsible for developing appropriate and user-responsive types, locations, and capacities of charging infrastructure on the road network.

Three specific EV charging modes are discussed in the literature: the static charging parked EV via cable and vehicle connector (e.g., charging station); wireless dynamic charging (e.g., wireless charging) where an in-pavement charger charges the battery as vehicle drives on the lane (Morris, 2015); battery swapping, where a depleted battery is replaced by a fully-charged one. Battery swapping requires significant space for the swapping supplies, equipment, and the swapping operation (Adler & Mirchandani, 2014) and standardized batteries and battery platform design. This can be achieved through cooperation among the OEMs (Liu and Wang, 2017).

Static charging is the most common charging method and has three categories. The first category (charging with AC 120 voltage outlet with 20-hr maximum charging time) seems to be most suitable at residences. The second category (charging with AC 280 voltage outlet with 7-hr maximum charging time), seems to work best at public parking locations. The third category (480 Volt AC/DC capacity) charges the EV as quickly as 20 minutes. Nevertheless, this charging time can hardly compete with the conventional (gasoline fueled) ICEV that is often refilled within 5 minutes (Liu & Wang, 2017; Tabesh et al., 2019).

Wireless dynamic charging (referred to as wireless charging in this chapter), is another EV charging technology. EVs that use this technology do not require charging cable and connector.

With wireless charging, the battery power needed for propulsion is reduced because the EV can obtain the electrical energy from the pavement (Morris, 2015), which can significantly reduce the EV initial cost (Ko & Jang, 2013). Further, the reduction in the needed battery weight causes the overall vehicle weight to decrease, and thus, increased propulsion power of the EV. Depending on their link locations, wireless charging facilities can significantly increase the EV driving range. Wireless charging offers EVs a potentially unlimited driving range if the vehicle is operating on the charging lane. Wireless-charging facilities can yield benefits in terms of simplicity, reliability, and ease-of-use compared to static charging (Barth et al., 2011; Haddad et al., 2019), and the efficient and reliable charging they provide can encourage patronage of EVs. However, wireless charging facilities are costly to construct, maintain, and operate (Gill et al., 2014) and have problems of electromagnetic compatibility, limited transfer of power, and lower efficiency due to the air-gap distance between the source and receiver (Covic & Boys, 2013; Moon et al., 2014).

In addition, wireless-charging lanes could end up as congested spots in the network as EVs may be attracted to them for purposes of convenient recharging, or acquiring a higher driving range, or both. Researchers have determined that these lanes can reduce the road capacity by 8%–17% and increase travel time (He et al., 2018). Table 2.1 summarizes the merits and demerits of different EV-related infrastructure development options considered in this chapter.

Table 2.1 Merits and demerits of different types of EV-related facilities

Facility	**Merits (Potential to ---)**	**Demerits (May cause ---)**
Construct new static charging stations	Address the current inadequacy of charging facilities Help reduce the range anxiety	Significant charging delay
Install wireless-charging facilities at general-purpose and/or AV-exclusive lanes	Address the current inadequacy of charging facilities Help reduce the range anxiety Eliminate charging delay Reduce the initial EV cost through battery downsizing	High cost of construction, maintenance, and operations Congestion at the wireless-charging lanes
Convert general-purpose lanes (EAV, EHDV, CHDV) to AV-exclusive lanes (EAV)	Preclude ROW acquisition and construction Separate AVs from HDVs and increases road capacity for AVs Promote AV ownership/use	Appropriation of capacity originally available to HDVs

2.1.5 Providing charging facility for EAV: business model development use charging lane as illustration

To bring the wireless charging facility to market, a business model must be developed, which includes determining the costs, revenues needed, and how revenues will be generated. A basic business model related to the deployment of wireless charging lanes was developed by Bernecker et al. (2020). According to this model, the public-sector IOO funds the installation, maintenance, and operations of the wireless charging facility, owns the road, and is in charge of road operations, and the private-sector IOO provides the electric infrastructure and, depending on the terms of the contract, provide the services for operating and maintaining the facility. Public access to the road is generally free in this model. Therefore, any vehicle that is technically compatible could use it and simply pay an energy bill which is generally calculated based on the amount of energy used. Table 2.2 summarizes the IOO stakeholder roles in this business model.

Table 2.2. IOO stakeholder roles in the business model

	Stakeholders and their typical responsibilities	
	Public-sector IOO	Private-sector IOO
Asset ownership	Wireless charging lanes (pavement)	Electric charging infrastructure
Cost(s) incurred	Installing wireless charging facilities	Construction, maintenance, operation
Revenue source(s)	System concession amounts paid by the private sector IOO	Energy bills paid by customers (road users)

2.2 Problem Statement

Research is needed to promote EVs by providing models and demonstrating analysis results that could help the transport agencies evaluate various EV infrastructure investments. This could be done by considering different types, locations, and capacities of charging facilities while striking a balance between agency investment and travelers' delay. During the transition phase, there will exist a mixed fleet (AVs and HDVs). It is needed to develop an optimal plan that minimizes the facility's cost (including the installation cost for both static and wireless-charging facilities) and user cost including the total travel time. Range constraints could be considered for electric HDVs and EAVs.

2.3 Objectives of this Part of the Report

The main objective of Part 1 of this report is to provide a comprehensive framework to determine the locations and capacities of charging facilities proposed to serve a mixed fleet of HDVs and AVs. To address this objective, the chapter uses a bi-level structure in which, at the upper level, the public and private sector IOOs seek to minimize the construction cost and total user cost (system travel time) subject to budgetary limitations. At the lower level, travelers select the route and vehicle type (AV vs. HDV) considering the EV driving range and link travel times. The proposed framework can enable the IOOs to understand the impacts of investment budgets on AV market penetration. Further, the methodology helps assess the impacts of wireless-charging facility installation (at general-purpose and AV-exclusive lanes) on travelers' route choices and vehicle type choices. This report considers intracity trips only and does not consider transit (bus) wireless charging facilities.

2.4 Scope of this Part of the Report

This part of the report (see Davatgari, 2021) considers the following types of decision-makers: the IOO (often, the transport agency's planner or policy maker that decides the recommended (optimal) locations and capacities of static and wireless-charging facilities for mixed fleet of AV and HDV; and the IOO (often, the private sector) that provides the funding, and constructs the EV charging facilities. In this chapter, these two types of decision makers are collectively considered as the primary decision maker at the upper level and referred as "the transport decision-maker". Also, in the context of this chapter, AV-exclusive lane deployment assumes that there exist an adequate number of lanes overall, and will involve the appropriation of one or more existing lanes for exclusive use by AVs and thus will not lead to an increase in the overall number of lanes in the corridor. In other words, the AV-dedicated lane will not need acquisition of right of way and new construction.

CHAPTER 3 LITERATURE REVIEW

In this chapter, a review of existing literature was carried out to identify and discuss past research on the synergies between EA and AV, the EV charging facility planning problem, and the economic and operational impacts of EV charging facility deployment. Also, past work on AV-exclusive lane impacts is discussed in this chapter.

3.1 Literature on EV and AV Synergies

There is a vast body of literature on the individual topics of electric vehicles (EVs) (Jochem et al., 2015; Xu et al., 2020) and autonomous vehicles (AVs) (Duarte & Ratti, 2018; González-González et al., 2019; Kopelias et al., 2020). However, very few studies have focused on Autonomous Electric Vehicles (AEVs), also referred to as Electric Autonomous Vehicles (EAVs). As an AV and EV synergy, Electric Autonomous Vehicles (EAVs) embody the advantages of both vehicle autonomy and electric propulsion. With their sensors and V2X connectivity capabilities, AVs can travel at reduced headways and consequently improve traffic mobility, which can help to save energy (Fagnant & Kockelman, 2015). Also, electric propulsion is expected to significantly reduce GHG emissions over a lifetime compared to ICEVs (Xu et al., 2020), and achieve comparable performance with less energy (Chau & Chan, 2007). Therefore, AEVs are generally expected to significantly reduce GHG emissions compared to HDVs which are mostly ICEVs. In Section 13.2, the report presents additional discussion on EV-AV synergies.

3.2 Literature on EV Charging Facility Planning

An EAV charging facility supplies electrical energy to charge electric AVs. To help mitigate the barriers to electric propulsion adoption for AVs, it is important to address optimal locations, charging levels, and types of charging facilities. There exist three levels of charging: levels 1 and 2 (slow charging) and level 3 (fast charging). A few studies have studied slow charging (Frade et al., 2011; Jia et al., 2014). Frade et al. (2011) introduced a model for locating slow-charging facilities to optimize demand coverage within level-of-service constraints. In recent years, several studies have focused on the optimal planning of fast-charging facilities (Amjad et al., 2018; Domínguez-Navarro et al., 2019; García-Villalobos et al., 2014; Miralinaghi, Keskin, et al., 2016; Sadeghi-Barzani et al., 2014). Navarro et al. (2019) modeled the network location design of an EV fast-charging facility to improve profitability through energy consumption reduction.

Regarding charging facility types, most studies consider static charging stations (Arslan & Karaşan, 2016; Chen et al., 2013; Ghamami et al., 2020; Huang et al., 2015; Lee & Han, 2017; Zheng et al., 2017; Zhu et al., 2016). Relatively few studies considered wireless-charging facilities (Chen, 2016; He et al., 2013; Liu & Wang, 2017; Riemann et al., 2015). He et al. (2013) presented a mathematical model to determine the optimum prices of electricity for wireless-charging lanes to maximize social welfare.

3.3 Literature on EV Charging Facility Location

There is a vast body of literature on the general problem of facility location in transportation (Abareshi & Zaferanieh, 2019; Lin & Lin, 2018; Melo et al., 2009). However, relatively few studies have explicitly addressed facility location in the specific application context of EV charging facilities. Riemann et al. (2015) investigated the optimal location of wireless-charging facilities to maximize network traffic flow, considering users' route choices. Chen et al. (2016) developed a user equilibrium based wireless-charging lane deployment model to optimize wireless-charging lane locations within a given budget. More recently, Liu et al. (2017) proposed a model for prescribing the locations of static and dynamic charging facilities to maximize social welfare, and to minimize total system travel time and the penalty for "failed" trips (caused by insufficient remaining battery charge). Although they considered multiple types of charging facilities and EVs, Liu et al. (2017) assumed that a vehicle can use only one (not both) of the charging facility types at a time. Based on the route choice behavior of the travelers (EV users), EV charging facility location studies can be classified into two groups.

The first group addresses the location of EV charging facilities from a purely planning perspective without considering operational elements such as network user equilibrium (UE). In other words, these studies do not consider travelers' route choices and link travel times. Also, these studies are more appropriate for intercity trips where travelers' route choice do not significantly impact travel times (Arslan & Karaşan, 2016; Ghamami et al., 2016; Hosseini & MirHassani, 2015; Huang et al., 2015; Li et al., 2016; Wang et al., 2016; Wang & Wang, 2010; Wu & Sioshansi, 2017). Ghamami et al. (2016) designed the location of charging facilities on intercity trips road links and therefore did not consider the impact of congestion. Yang et al. (2017) also considered long-distance travel routes in a region. In their study, battery-swapping station locations were modeled to maximize the total benefit of battery leasing. Due to the long distances of trips, they assumed travelers' travel time as constant, and did not consider the impact of charging facility location on congestion. Using a similar approach, Wang et al. (2016) modeled the charging facility location problem for charging stations and developed construction schedules for EV charging stations assuming constant paths for each EV. All these studies broke new ground in the context of the EV charging facility location problem. However, for certain kinds of networks such as urban road systems, consideration of planning perspectives only and no operationslevel considerations (traffic congestion and user equilibrium, for example), can be considered rather too restrictive and needs to be addressed.

The second group discusses the location planning of charging facilities in metropolitan areas and therefore consider congestion effects and travelers route choices (Chen et al., 2013; Chen, 2016; Ghamami et al., 2020; Liu & Wang, 2017; Miralinaghi, Lou, et al., 2016). In this group of studies, the researchers considered transportation network user equilibrium. For example, Zheng et al. (2017) accounted for network user equilibrium and the traffic congestion impact of alternative sets of charging station locations.

3.4 Literature on Impacts of AV-Exclusive Lanes

AVs are expected to have a beneficial effect on road network capacity (Dong et al., 2020; Ha, Chen, Du, et al., 2020). Tientrakool et al. (2011) demonstrated that a traffic stream with AV-exclusive lanes can operate with reduced headways, allowing a 43% increase in the road capacity. They also showed that a traffic stream consisting of connected AVs can increase the road capacity by up to 273%. In addition, regarding the potential travel time benefits of AVs, several studies have shown that automation can improve the performance of intersections (Arvin et al., 2021). Hoogendoorn et al. (2014), in a review paper, suggested that AVs could reduce intersection congestion by 50%. AVs are considered one of those technologies that could engender significant changes in mobility (Dong et al., 2020).

Many studies have investigated AV traffic impacts using simulation tools. Van Arem et al. (2006) simulated AVs operations to study the impact of AV-exclusive lanes, and found that average operating travel speed is influenced by AV market penetration. Also, Talebpour et al. (2017) explored CAV impacts by modeling CAVs (using the Cooperative Adaptive Cruise Control (CACC) algorithm) and HDVs (using the Intelligent Driver Model (IDM)) and confirmed that travel time is influenced significantly by AV market penetration. They showed that with low AV market penetration, the system-level travel impacts are small; however, this problem can be addressed by implementing AV-exclusive lanes. Chen et al. (2016) studied the AV-exclusive lane location problem with the active-set algorithm, with the objective of minimizing total system travel time. In their study, AV market penetration was estimated as a function of AV-exclusive lane deployment. In this context, Liu and Song (2019) stated that there could be uncertainty in the flow distributions due to AV impacts on road capacity. They used Genetic Algorithms (GA) methods to solve the problem of AV-exclusive lane location in the worst-case traffic flow distribution.

It is also expected that AVs will have a beneficial economic effect in terms of reducing the value of time (VOT). Relatively few studies have examined the impact of AVs on the VOT of travelers (Correia et al., 2019; Cyganski et al., 2015). Cyganski et al. (2015) conducted a survey and confirmed that respondents that tend to work while commuting were more likely to work while commuting in an AV. Most of the respondents agreed that while riding in the AV, the tasks they typically perform while driving the HDV will become important. Using various AV-growth scenarios in the Netherlands, Correia et al. (2019) reported a potential VOT decrease of between 1% and 31% for AV users (in vehicle automation levels 3 and higher).

3.5 Literature on Tradeoffs

A vast body of literature have studied the tradeoff analysis in the context of transportation asset management (Bai et al., 2012, 2015; Bai & Labi, 2008; Gharaibeh et al., 2006; Mrawira & Amador, 2009). However, in the context of EV charging facility planning, only a few studies have analyzed tradeoffs (Nie & Ghamami, 2013; Woo et al., 2021). Nie et al. (2013) considered the tradeoff between EV charging facility construction cost and manufacturing batteries. They also explicitly considered the levels of service experienced by EV users in the form of recharging delay. Woo et al. (2021) analyzed the tradeoff between the EV charging facility construction cost and quality of service.

3.6 Literature Review on Wireless Charging Facility Investment Business Models

Only a few studies have considered business models for wireless charging facilities. In the literature, it is suggested that the business model for wireless charging facility will likely take the form of a public-private partnership. According to Bateman et al. (2018), the capital cost and investment risk are too high and therefore precludes most private-sector investors from being the sole investors. Government funding is required because the government is more likely to accept longer payback times compared to private investors, and is more likely to be interested in investments in technologies that yield emissions reduction.

Bernecker et al. (2020) studied two models: (1) wireless charging facility as a classic highway and (2) wireless charging facility as a service. In the first model, access to the wireless-charging road was assumed to be available, and any compatible vehicle could use it and simply pay the energy bill. According to this model, a transportation agency funds the installation of the wireless charging facilities, owns the road, and is responsible for road operations, while the electric component of the infrastructure is provided and maintained/ operated by private sector investors. In the second model, access to the wireless-charging road is available only to those customers who pay for access, similar to a toll road.

3.7 Research Gaps and Contributions

The aforementioned studies provided a solid pioneering foundation in this research area, and addressed several aspects related to EV charging facility planning. However, there is a need for a framework for EV charging facility problem in the transition phase where there will exist a mixed fleet of AVs and HDVs. This framework is developed primarily from the perspective of the IOO and considers the perspectives of road users (in terms of their travel time). The study addresses EV charging investment decisions: facility types, locations, and capacities. The objective (total travel time cost minimization) is made subject to range constraints for both HDVs and AVs that are all assumed to be EV. The proposed framework enables the agency to understand the impacts of varying investment budgets on AV market penetration. Further, the methodology determines the impacts of installing wireless-charging facilities on general-purpose and AV-exclusive lanes on travel and vehicle-type choice of travelers. The contributions of this chapter are threefold. First, the study addresses the optimal location of EV charging facilities considering a mixed electric fleet (AV and HDV). Second, this study considers the possibility of EVs during a single trip to be recharged at wireless-charging guideway or at charging stations. This contrasts with the current studies in literature that assume EVs can be charged at only one (not both) types of charging facility. Third, this study considers the possibility of installing wireless-charging facilities at either AV-exclusive lanes, or general-purpose lanes, or both.

Table 3.1 Past Studies on Electric Charging Facilities: A Comparison

Reference	Vehicle type **(**AV/HDV**)**	Charging mode	Charging speed	Study objective	User equilibrium
Ghamami et al. (2020)	HDV	Static	Fast charging	Minimize infrastructure cost and users' detour, waiting, and charging delay.	Yes
He et al. (2018)	HDV	Static	Fast charging	Maximize path flows that patronize the charging stations.	Yes
Lee et al. (2017)	HDV	Static	Fast charging	Maximize the total sum of flows covered while minimizing the number of recharging stations.	Yes
Liu and Wang (2017)	HDV	Static and dynamic	Fast charging	Maximize social welfare (by minimizing sum of total system travel time and penalty fee for "failed" trips).	Yes
Zheng et al. (2017)	HDV	Static	Fast charging	Minimize total system travel time and energy use.	Yes
Chen et al. (2016)	HDV	Dynamic	N/A	Minimize total system travel time.	Yes
Zhu et al. (2016)	HDV	Static	Fast charging	Minimize the total charging station construction costs. Attain a desired traveler convenience.	Yes
Yang et al. (2017)	HDV	Battery swapping	N/A	Maximize total benefit from the battery leasing/electric car-sharing service business operational and construction costs.	No
Ghamami et al. (2016)	HDV	Static	Fast charging	Minimize sum of infrastructure cost, total time spent on charging battery, queuing delay at each station and battery cost of PHEV.	No
Li et al. (2016)	HDV	Static	Fast charging	Minimize total cost of new charging stations and relocations during planning horizon.	No
Wang et al. (2016)	HDV	Static	Fast charging	Minimize total operational and construction costs.	No
Arslan and Karasan (2016)	HDV	Static	Fast charging	Minimize total traveled distance.	No

This study (Part 1)	**AV/HDV**	**Static and dynamic**	**Fast charging**	**Minimize total system travel time and construction cost of EV charging infrastructure (lanes and stations).**	**Yes**

CHAPTER 4 METHODOLOGY

This chapter begins with an introduction that summarizes the proposed bi-level framework, followed by the preliminary settings and assumptions made in the study. Each level of the framework is then described in detail.

4.1 Introduction

The EV charging facility location problem is formulated as a bi-level program consisting of upper-level and lower-level models. The bi-level framework is widely used in transportation planning literature to solve network design and facility location problems (Miralinaghi, Keskin, et al., 2016; Seilabi et al., 2020). At the upper-level, the transportation agency decision-makers seek to minimize construction cost and total system travel time cost. The control (decision) variables are the location and operating capacities of the EV charging facilities, subject to the budgetary limitations. As mentioned earlier, the transportation decision-makers provide AV-exclusive lanes to motivate AV patronage through reduction of AV travel time, particularly at wireless-charging lanes, as well as other reasons including safety.

At the lower level, travelers seek to address their travel needs subject to EV driving ranges while minimizing their travel time. The travelers' decisions are the choices of route and vehicle type (AV/HDV). When the transport decision-makers promote the construction of EV charging facilities, travelers respond by purchasing AV/HDV and changing their routes to reduce their travel times on trips subject to the EV driving range. Under user equilibrium condition, travelers are unable to further reduce their travel times by unilaterally changing their routes. Therefore, the route choice of AV/HDV travelers depends on their travel times and driving ranges. In other words, the routes selected by the travelers need to be consistent with the specified EV driving range or contain nodes/links with EV charging facilities.

4.2 Preliminaries

$G = (N, A)$ represents the urban road network where N and A denote the set of nodes and links, respectively. A' and $\bar{A}$ denote the set of AV-exclusive lanes and general-purpose lanes, respectively. Let V indicate the type of vehicle set ($v = 1, 2$ for HDV and AV travelers, respectively). K represents a set of candidates charging station nodes ($k \in K$), and K' represents a set of candidate links for wireless charging ($k' \in K'$). In addition, O and D denote a set of origins, destinations with indices r and s, respectively. Sets O, D, K, and K' are a subset of N and the sets

A' and $\bar{A}$ are a subset of A. Consistent with the Bureau of Public Roads function, the travel time at link $(i, j) \in A$ can be written as:

$$t_{ij}(x_{ij}) = t_{0,ij}\left(1 + 0.15\left(\frac{x_{ij}}{\chi_{ij}}\right)^4\right) \qquad \forall (i,j) \in A \qquad 4.1$$

where $t_{0,ij}$ and χ_{ij} denote the free-flow travel time and capacity of the link (i, j), respectively. The summary of the notations used in this part of the study is presented in Table 4.1.

This chapter considers that charging stations have a certain level of operating capacity. The EV charging station operating capacity is discussed in the following section in detail. To capture the impact of charging delay and the operational capacity of stations, the traffic network configuration is modified as follows: For candidate nodes with charging stations, a dummy node and two dummy links are established. The set of dummy candidate nodes for charging stations is represented by N^D. A^D denotes the set of dummy links. Sets N^D and A^D are a subset of N and A, respectively. The network transformation is illustrated in Figure 4. 1. Figure 4 1(a) represents the original network where the charging station is located on node i. To capture the impact of charging delay, we include dummy node i' with the charging station (Figure 4 1(b)). Then, two dummy links (i',i) and (i, i') are introduced. The capacity and travel time of the dummy link (i, i') is equal to the capacity and charging delay of the charging station at candidate node i, respectively. The length of each dummy link is set to zero to ensure that it does not impact the driving range.

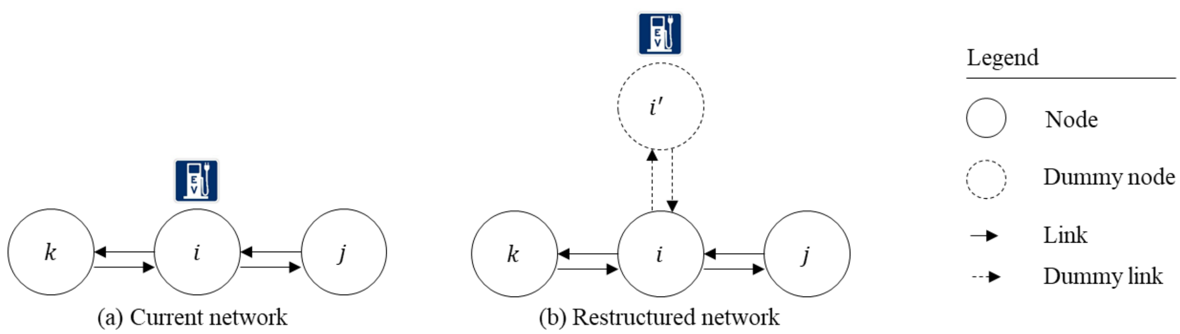

Figure 4.1 Transformation of the road network at nodes with charging stations

4.3 Assumptions

A few assumptions were made in this part of the study that can be considered realistic. First, the mixed fleet of AV and HDV is considered to be electric. This is an important assumption because the literature suggests that AVs will be introduced into the market when the EV market share is high (Lam et al., 2018). Second, only AV travelers are expected to patronize AV-exclusive and general-purpose lanes, and HDV travelers can patronize general-purpose lanes only. This assumption is important because separating AVs and HDVs through the deployment of AV-exclusive lanes is considered as an effective method to amplify the benefits of AVs and promote their adoption (Liu & Song, 2019; Ha, 2019; Seilabi et al., 2020).

Further, it is assumed that AVs are all private and personal vehicles not shared. This assumption is important because the recharging needs of shared AVs are often different from that of privately-owned AVs. Third, it is assumed that the transportation decision-maker considers varying levels of charging station capacity. y_k is an integer variable representing the capacity level of the charging station located at candidate node k. $y_k > 0$ indicates the electric charging station of node k operates at level y_k and $= 0$ indicates that electric charging station is not available at node k. For example, $y_k = 1$ for level 1, $y_k = 2$ for level 2, and so on. Let γ_k denote the given charging station capacity level 1 at candidate node k. Hence, the capacity and construction cost of level y_k charging station in node k are $y_k \cdot \gamma_k^1$ and $\mathrm{F}(y_k)$ respectively. $\mathrm{F}(y_k)$ is assumed to be a linear function of y_k and captures scale economies, as follows:

$$\mathrm{F}(y_k) = \iota_1 + \iota_0 \cdot y_k \cdot \gamma_k^1 \qquad \forall k \in K_1 \qquad 4.2$$

where ι_0 and ι_1 represent the variable cost and fixed cost, respectively, of constructing a charging station at level y_k.

For wireless-charging lanes, it is assumed that the capacity is equal to the capacity of the corresponding lane. Let $z_{k'}$ equal to 1 if there exist a wireless-charging lane at candidate link k' and 0 otherwise. As discussed earlier, $\chi_{k'}$ denotes the given traffic capacity of the corresponding lane. Hence the traffic capacity and installation cost of the wireless-charging lane at link k' is equal to $z_{k'} \cdot \chi_{k'}$ and $F'(z_{k'})$, respectively. $F'(z_{k'})$ is assumed to be a linear function of $z_{k'}$ and captures scale economics, as follows:

$$\mathrm{F}'(z_{k'}) = \pi_1 + \pi_0 \cdot z_{k'} \cdot \chi_{k'} \qquad \forall k' \in K' \qquad 4.3$$

where π_0 and π_1 represent the variable and fixed cost, respectively, of installing a wireless-charging facility at link k'.

Fifth, it is assumed that the AV-exclusive lane locations have already been established by the transportation agency prior to this analysis and therefore is not a variable in the model. To capture the impacts of increased capacity and decreased free-flow travel time (due to AV capabilities) at AV-exclusive lanes compared to general-purpose lanes, a dummy link is established. The network transformation is illustrated in Figure 4.2. Figure 4.2(a) represents the original network where the AV-exclusive lane is located at link (i, j). To capture the impact of AV-exclusive lane, we replace it conceptually with a dummy link (i, i', j) (Figure 4.2(b)). The capacity and free-flow travel time of the dummy link (i, i', j) is equal to the capacity and free-flow travel time of AV-exclusive lane, respectively.

Sixth, at the lower-level model, it is assumed that the equilibrium path/link flows can be interpreted as the average conditions representing the steady-state network (Miralinaghi et al., 2020). As a result, possible temporal fluctuations (e.g., day-to-day or within-a-day) are not captured in the model developed in this chapter. Finally, it is assumed that the amount of electricity needed to complete the trip on a path is not a function of traffic flow because travelers cannot predict the relation between energy consumption and traffic flow (Chen, 2016; Liu & Wang, 2017). Hence, it is assumed that the electricity consumption of EVs is only a function of travel distance.

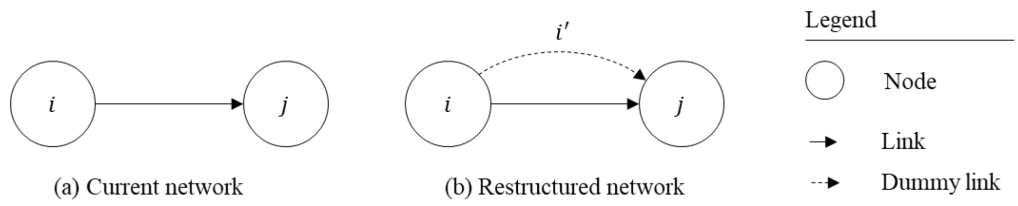

Figure 4.2 Transformation of the road network at links with AV-exclusive lane

4.4 The Bi-level Model

The EV charging facility location problem is formulated as a bi-level program consisting of upper-level and lower-level models (Figure 4.3). At the upper-level, the transportation decision-makers seek to minimize total system travel time cost subject to budgetary limitations. The control decision variables are the location and operating capacities of the EV charging facilities. As mentioned earlier, the transportation decision-makers provide AV-exclusive lanes to motivate AV patronage through reduction of AV travel time, particularly at wireless-charging lanes, as well as other reasons including safety. At the lower level, travelers seek to address their travel needs subject to EV driving ranges while minimizing their travel times. The travelers' decisions pertain to the selection of the route and vehicle type (AV/HDV).

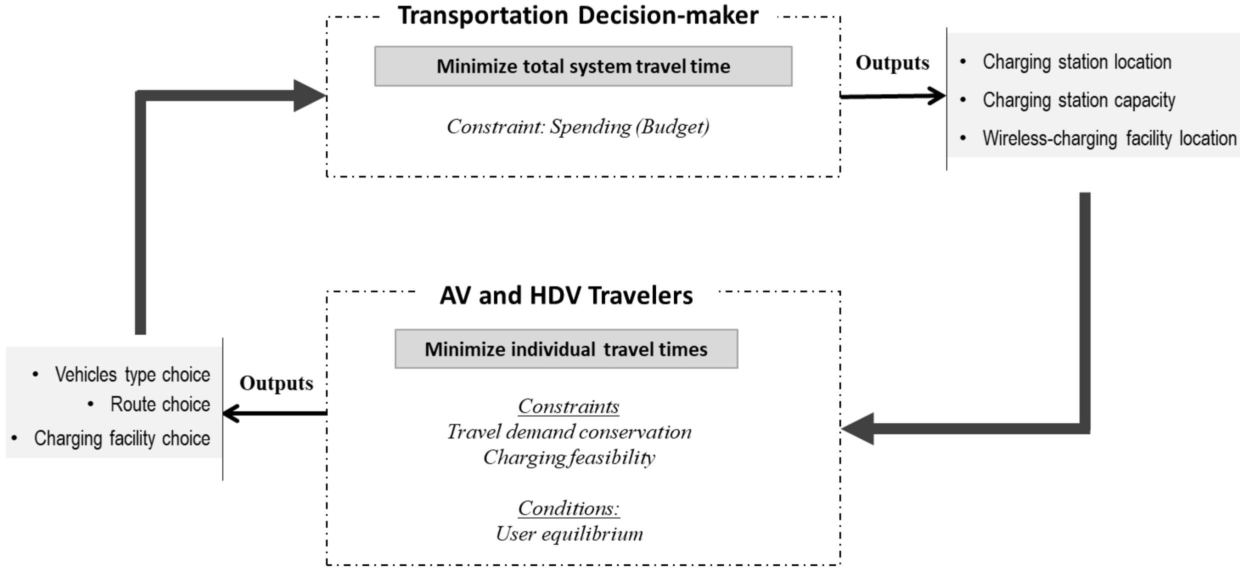

Figure 4.3 Bi-level nature of the framework

Table 4.1 Summary of notations (For Part I of this report)

Sets	
$\boldsymbol{N}$	Set of nodes on the road network ($i \in N$)
$\boldsymbol{A}$	Set of links on the road network ($(i,j) \in A$)
$\boldsymbol{A'}$	Set of AV-exclusive lanes ($(i,j) \in A'$)
$\bar{\boldsymbol{A}}$	Set of general-purpose lanes ($(i,j) \in \bar{A}$)
$\boldsymbol{V}$	Set of vehicle types (AVs: $v = 1$, HDVs: $v = 2$)
$\boldsymbol{O}$	Set of trip origins ($r \in O$)
$\boldsymbol{D}$	Set of trip destinations ($s \in D$)
$\boldsymbol{K}$	Set of candidate nodes for charging station locations ($k \in K$)
$\boldsymbol{K'}$	Set of candidate lanes for wireless charging ($k' \in K'$)
$\boldsymbol{N^D}$	Set of dummy nodes on the road network
$\boldsymbol{A^D}$	Set of dummy links on the road network
Parameters	
$\boldsymbol{B}$	Construction budget, \$
$\boldsymbol{t_{0,ij}}$	Free-flow travel time at link (i,j), minutes
$\boldsymbol{\chi_{ij}}$	Capacity of link (i,j), veh/hr
$\boldsymbol{L_{i,j}}$	Length of link (i,j), mile
$\boldsymbol{R_{i,j}}$	Recharging rate of charging link (i,j), kw/hr
$\boldsymbol{d^{r,s}}$	Travel demand of origin-destination (r,s)
$\boldsymbol{\theta^{v}}$	Value of time of EV type v users, \$/hr
$\bar{\boldsymbol{R}}$	Maximum driving range of vehicles, mile
$\bar{\bar{\boldsymbol{R}}}$	Initial driving range of vehicles, mile
$\boldsymbol{C_v}$	Purchase price of EV type v, \$
Variables	
$\boldsymbol{t_{ij}}$	Travel time of vehicles on link (i,j), minutes
$\boldsymbol{x_{ij}}$	Aggregate traffic flow of vehicles on link (i,j), veh/hr
$\boldsymbol{z_{k'}}$	Binary variable, $= 1$ if the wireless-charging facility is available on candidate link k'; $= 0$ otherwise
$\boldsymbol{y_k}$	Integer variable representing the capacity level of charging station located at candidate node k, $y_k \in \{0,1,2,\dots,\varsigma\}$
$\boldsymbol{\mu_v^{r,s}}$	Observed minimum travel time of EV type v users travelling from origin r to destination s
$\boldsymbol{P_v^{r,s}}$	Percentage of users travelling from origin r to destination s choose EV type v
$\boldsymbol{d_v^{r,s}}$	Travel demand of EV type v users travelling from origin r to destination s
$\boldsymbol{e_{ij}^{r,s,v}}$	Binary variable, $= 1$ if link (i,j) is on the feasible path for EV type v travelling from origin r to destination s; $= 0$ otherwise
$\boldsymbol{x_{ij}^{r,s,v}}$	Flow of EV type v on link (i,j) travelling from origin r to destination s
$\boldsymbol{\eta_i^{r,s,v}}$	Travel time of EV type v travelling from origin r to destination s
$\boldsymbol{b_j^{r,s,v}}$	Driving range of EV type v travelling from origin r to destination s
$\boldsymbol{r_{ij}}$	$= R_{ij}$, charging rate of charging link (i,j), if charging facility is available on the link (i,j); $= 0$ otherwise

3

4.4.1 The Upper-Level Model

As mentioned earlier in this chapter, at the upper level, the transportation decision-makers consider candidate locations of charging stations (at nodes) and wireless-charging facilities (at links) and their operating levels and seek to minimize the total travel time cost. The upper-level model can be formulated as follows:

$$\min Z^U = \sum_{(i,j)\in A} \theta^v t_{ij}\left(x_{ij}^v\right)x_{ij}^v \tag{4.4}$$

$$\sum_{k\in K} \mathrm{F}(y_k) + \sum_{k'\in K'} \mathrm{F}'(z_{k'}) \leq B \tag{4.5}$$

$$x \in x^{\text{lower level}}, t \in t^{\text{lower level}} \tag{4.6}$$

$$y_k \in \{0,1,2,\dots,\varsigma\} \qquad \forall k \in K \tag{4.7}$$

$$z_{k'} \in \{0,1\} \qquad \forall k' \in K' \tag{4.8}$$

where ς is the maximum capacity level of charging stations, and B is the construction budget. The objective function (4.4) minimizes total system travel time cost. Constraint (4.5) ensures that the budget constraint for constructing the charging facilities is satisfied. Constraint (4.6) states that the link flows and travel times are derived from the lower-level model. Finally, constraints (4.7) and (4.8) specify the integer and binary domains of the upper-level decision variables, respectively.

4.4.2 The Lower-Level Model

The lower-level model is related to the route and vehicle type (AV vs. HDV) choices of travelers in response to the policies and actions of the transportation decision-maker at the upper level. To capture the vehicle type choice, a logit model with a utility function is applied to estimate the travel demand $d_v^{r,s}$ of vehicle type v (AV vs. HDV) between each origin r and destination d.

In the logit model, the AV market penetration depends on the travel time between each origin-destination pair and vehicle purchase prices. This model is used in the literature to capture travelers' vehicle type choices (Liu and Wang, 2017; Shabanpour et al., 2018). Let $u_v^{r,s}$, $P_v^{r,s}$, and $\mu_v^{r,s}$ represent the utility, probability, and the minimum travel time of users traveling from origin r to destination s choosing EV type v, respectively.

The logit model can be formulated as follows:

$$u_v^{r,s} = \frac{\beta_0 C_v}{YW} + \beta_1 \cdot \mu_v^{r,s} \qquad \forall (r,s) \in OD, v \in V \tag{4.9}$$

$$P_v^{r,s} = \frac{\exp(u_v^{r,s})}{\sum_{v \in V} \exp(u_v^{r,s})} \qquad \forall (r,s) \in OD, v \in V \qquad 4.10$$

$$d_v^{r,s} = d^{r,s} P_v^{r,s} \qquad \forall (r,s) \in OD, v \in V \qquad 4.11$$

Where:

β_0 and β_1 denote the weights for vehicle purchase price and travel time cost, respectively, Y and C_v represent the average life expectancy and the vehicle purchase price. W represents the users' average wage rate ($/hr). Equation (4.9) calculates the utility of users traveling from origin r to destination s that choose EV type v. Equation (4.10) calculates the probability of choosing EV type v of users traveling from origin r to destination s. Finally, Equation (4.11) calculates the travel demand for EV type v users traveling from origin r to destination s.

To capture the driving range feasibility in terms of EV recharging needs, this study modifies the constraints proposed by Zheng et al. (2017) to capture multiple types of EV charging facilities. The equilibrium condition can be achieved using a feasible subnetwork defined by $e_{ij}^{r,s,v}$ which is a binary variable that indicates whether the link (i,j) is on the feasible path based on the range constraint for EV of type v traveling from origin r to the destination s. Let $b_i^{r,s,v}$ denote the driving range of EV type v at node i traveling from origin r to destination s, and let r_{ij} represent the charging rate of the charging link (i,j). The EV driving range feasibility can be formulated as follows:

$$b_j^{r,s,v} \le b_i^{r,s,v} - L_{ij} + r_{ij} - M \cdot \left(1 - e_{ij}^{r,s,v}\right) \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad 4.12$$

$$b_i^{r,s,v} \le \bar{R} \qquad \forall i \in N, \forall (r,s) \in OD, v \in V \qquad 4.13$$

$$b_r^{r,s,v} = \bar{\bar{R}} \qquad \forall (r,s) \in OD, v \in V \qquad 4.14$$

$$r_{ij} = R_{ij} \cdot \left(z_{ij} + y_{ij}\right) \qquad \forall (i,j) \in A \qquad 4.15$$

$$b_i^{r,s,v} \ge 0 \qquad \forall i \in N, \forall (r,s) \in OD, v \in V \qquad 4.16$$

$$e_{ij}^{r,s,v} \in \{0,1\} \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad 4.17$$

$$z \in z^{\text{upper level}}, y \in y^{\text{upper level}} \qquad 4.18$$

where M is a large positive constant. L_{ij} denotes the length of link (i,j), and R_{ij} denotes the charging rate of the EV charging lane at link (i,j). $\bar{R}$ and $\bar{\bar{R}}$ denote the maximum and initial (pre-trip) driving range of vehicles. Constraint (4.12) derives the residual range of EVs of type v at node i traveling from origin r to the destination s. Constraint (4.13) ensures that the residual range of EVs does not exceed the maximum range of the vehicle. Constraint (4.14) ensures that the driving range of EVs is equal to the initial (pre-trip) driving range of vehicle at the trip origin. Constraint (4.15) ensures that r_{ij} is equal to the charging rate of charging lane at link (i,j) if charging facility is available at the link and is $= 0$ otherwise. Constraint (4.16) guarantees the non-negativity of the driving range, and constraint (4.17) specifies the binary domain of the $e_{ij}^{r,s,v}$. Finally, constraint (4.18) states that the decisions of the transport decision-makers are derived at the upper level. To capture the route choice behavior of travelers under the policies and actions of the transportation decision-maker in the upper level, a multi-class traffic assignment is developed. Let $\eta_i^{r,s,v}$ denote the minimum cost of EV type v to travel to node i traveling from origin r to destination s. The first-order conditions of conventional traffic assignment model can be written as follows:

$$x_{ij}^{r,s,v} \cdot \left(t_{ij}(x_{ij}) + \rho_{ij}^{r,s,v} + \eta_i^{r,s,v} - \eta_j^{r,s,v}\right) = 0 \quad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \quad 4.19$$

$$t_{ij}(x_{ij}) + \rho_{ij}^{r,s,v} + \eta_i^{r,s,v} - \eta_j^{r,s,v} \geq 0 \quad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \quad 4.20$$

$$x_{ij}^{r,s,v} \leq M \cdot e_{ij}^{r,s,v} \quad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \quad 4.21$$

$$\rho_{ij}^{r,s,v} \leq M \cdot \left(1 - e_{ij}^{r,s,v}\right) \quad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \quad 4.22$$

$$\eta_r^{r,s,v} = 0 \quad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \quad 4.23$$

$$e_{ij}^{r,s,2} = 0 \quad \forall (i,j) \in A' \cup A'', \forall (r,s) \in OD \quad 4.24$$

$$\sum_{j:(j,i)\in A} x_{ji}^{r,s,v} - \sum_{j:(i,j)\in A} x_{ij}^{r,s,v} = \begin{cases} -d_v^{r,s} & \text{if } i \text{ is the origin of OD pair} \\ 0 & \text{if } i \text{ is an intermediate node} \\ d_v^{r,s} & \text{if } i \text{ is the destination of OD pair} \end{cases} \quad \forall i \in N, \forall (r,s) \in OD, v \in V \quad 4.25$$

$$\rho_{ij}^{r,s,v}, x_{ij}^{r,s,v}, \eta_i^{r,s,v} \geq 0 \quad \forall (i,j), \forall w, \forall t, \forall m \quad 4.26$$

Constraints (4.19) and (4.20) are the user equilibrium conditions which ensure that the link (i,j) is on the feasible path based on the range constraint. Otherwise, there is an extra perceived cost for travelers which discourages their patronage of this link. Constraint (4.21) states that users can only use their corresponding feasible subnetworks. Constraints (4.22) state that if a link (i,j) does not belong to the feasible subnetwork, then there is an extra perceived cost ($\rho_{ij}^{r,s,v}$) for using the link (i,j). Constraint (4.23) ensures that minimum cost of EV type v at the starting node is equal to zero. Constraint (4.24) ensures that the HDV travelers do not use AV-exclusive link. Constraint (4.25) indicates the conservation constraint. Finally, Constraint (4.26) guarantees the non-negativity of the link flows.

4.5 Tradeoffs

A tradeoff can be described as "sacrifice of a physical entity of quality in return for gaining another" (Bai et al., 2012). Many decision-making frameworks benefit from tradeoff analysis. In transportation asset management, the decision-makers often encounter a need to quantify the tradeoffs (Bai et al., 2012). In the context of this chapter, there are many types of tradeoffs, as seen in the following cases:

- The tradeoff between EV charging facility construction investment level and user travel time cost: if few EV charging facilities are constructed, this will cause EV user delay and higher travel time costs and, consequently, user dissatisfaction. On the other hand, if too many charging facilities are constructed, this will lead to excess idle time and, consequently, underutilization of capacity, and waste of cost resources. Therefore, a good balance should be achieved between agency savings and user benefits.
- The tradeoff between EV charging facility construction investment level and AV/HDV market penetration. This tradeoff is difficult to analyze because the AV/HDV market penetration depends on the user travel time and vehicle purchase price. With increasing the EV charging facility construction investment level, the user travel time decreases. As a result, the AV market penetration decreases because the AV purchase price is typically higher compared to the HDV purchase price. On the other hand, in the literature, it is suggested that in the future, the AV purchase price will decrease because of technological advancements (Shabanpour et al., 2018). Considering the same value for AV and HDV purchase price, increasing the EV charging facility construction investment level decreases the user travel time. As a result, AV market penetration increases because the travel time for AV users is typically lower (due to AVs' capabilities) compared to travel time for HDV users.
- The tradeoff between AV and HDV user travel time costs: if the agency provides the EV charging facilities only for AV users (at AV-exclusive lanes), the travel time for AV users decreases, but the travel time for HDV users decreases. On the other hand, the provision of EV charging facilities at general-purpose lanes will increase the travel time for AV users because AV users will need to deviate from their optimal route (including AV-exclusive lanes) to recharge.

4.6 Summary of the Chapter

This chapter presented the methodology for (part 1 of this study). First, Section 4.1 introduced the framework for solving the problem, and Section 4.2 presented the preliminaries. The assumptions made in this study were discussed in detail in Section 4.3. The upper-level and lower-level models were represented in sections 4.4.1 and 4.4.2, respectively. The transportation decision-maker's decisions are modeled using the upper-level model, and the travelers' route choice and vehicle type choice are modeled using the lower-level models. In Section 4.5, some tradeoffs associated with the problem, are discussed.

CHAPTER 5 SOLUTION ALGORITHM

In this chapter, the solution algorithm for the proposed bi-level model is discussed. This chapter begins with an introduction to the solution algorithm. Then, subsequent chapters describe in detail, solution approach for each level.

5.1 Introduction

The proposed bi-level model consists of the upper level and lower level, as discussed earlier. The bi-level model developed is inherently complicated to solve and can be described as NP-hard (Bazaraa et al., 2013). In this chapter, the Non-Dominated Sorting Genetic Algorithm (NSGA-II), a type of evolutionary optimization search technique, is used to solve the upper-level model. NSGA-II is a type of GA proposed by Deb et al. (2002) that has been widely used to solve multi-objective network design problems (Alavidoost et al., 2018; Bai et al., 2012; Ceylan & Bell, 2005; Hosseininasab et al., 2018; Hosseininasab & Shetab-Boushehri, 2015; Mazloumi et al., 2012). At the lower level, for the traveler's vehicle type choice (AV vs. HDV) the fixed-point method suggested by Liu et al. (2017) is used, and for travelers' route choice, the Frank-Wolfe algorithm (1956) is used to solve the proposed user equilibrium model. For each of the two levels, the rest of this section provides a detailed description of the solution approach.

5.2 Solution Approach for the Upper-Level Model

In this section, NSGA-II is used to solve the upper-level model. NSGA-II is an iterative search method in which two previous solutions are combined to generate new solutions. This approach begins with a viable set of solutions known as population. For each solution in the population, called a chromosome, the objective value at the upper level is determined. Based on the objective value, the algorithm then selects individual chromosomes and uses crossover and mutation to generate the next generation of the population. For the new generation, this process is repeated until a pre-specified stopping criterion is met. The steps of the NSGA-II are stated below, and the algorithm flowchart is presented in Figure 5.2.

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1	2	...	n	$n+1$	$n+2$	...	$n+m$
z_1	z_2	...	z_n	y_{n+1}	y_{n+2}	...	y_{n+m}

Figure 5.1 Representation of each chromosome

Step 1: The initial population of multiple chromosomes, where each chromosome is a feasible solution, is generated to initialize the NSGA-II algorithm. A sample of chromosomes is shown in Figure 5.1. Each chromosome is a set of *n* candidate links for wireless charging and *m* candidate nodes for charging stations. Each cell represented chromosome in Figure 5.1, called gene, indicates the charging facility's capacity level and, if it is zero, the candidate location of the charging facility is not selected for construction. The random initialization method is used, and it has been ensured that the upper-level model constraints are met for each solution.

Step 2: The objective value of the upper-level model is determined for each chromosome. To do so, the construction cost is calculated at the upper level and total travel cost is calculated at the lower level.

Step 3: This algorithm updates the Pareto frontier in each iteration. If the number of iterations exceeds a threshold without improvement of the Pareto frontier, the algorithm will be terminated. Otherwise, the algorithm goes to the next step.

Step 4: In this step, the non-dominated sorting technique is used to sort the chromosomes that establish Pareto ranks. Then, based on the objective values, some chromosomes are chosen as parents. To do so, the Tournament and Rolette Wheel selection methods (Yadav & Sohal, 2017) are applied.

Step 5: As the leading genetic operator, crossover (Ono et al., 2003) combines parents to breed offspring where some of the parent chromosomes' characteristics are inherited in each offspring. The arithmetic crossover, which derives from the linear combination of chromosomes to generate new offspring, is used in this chapter. Then, the algorithm goes through a mutation mechanism in which the value of certain genes is changed in order to prevent them from being trapped in the local optima. The uniform integer mutation method is used to do this. Then, the algorithm goes to Step 2.

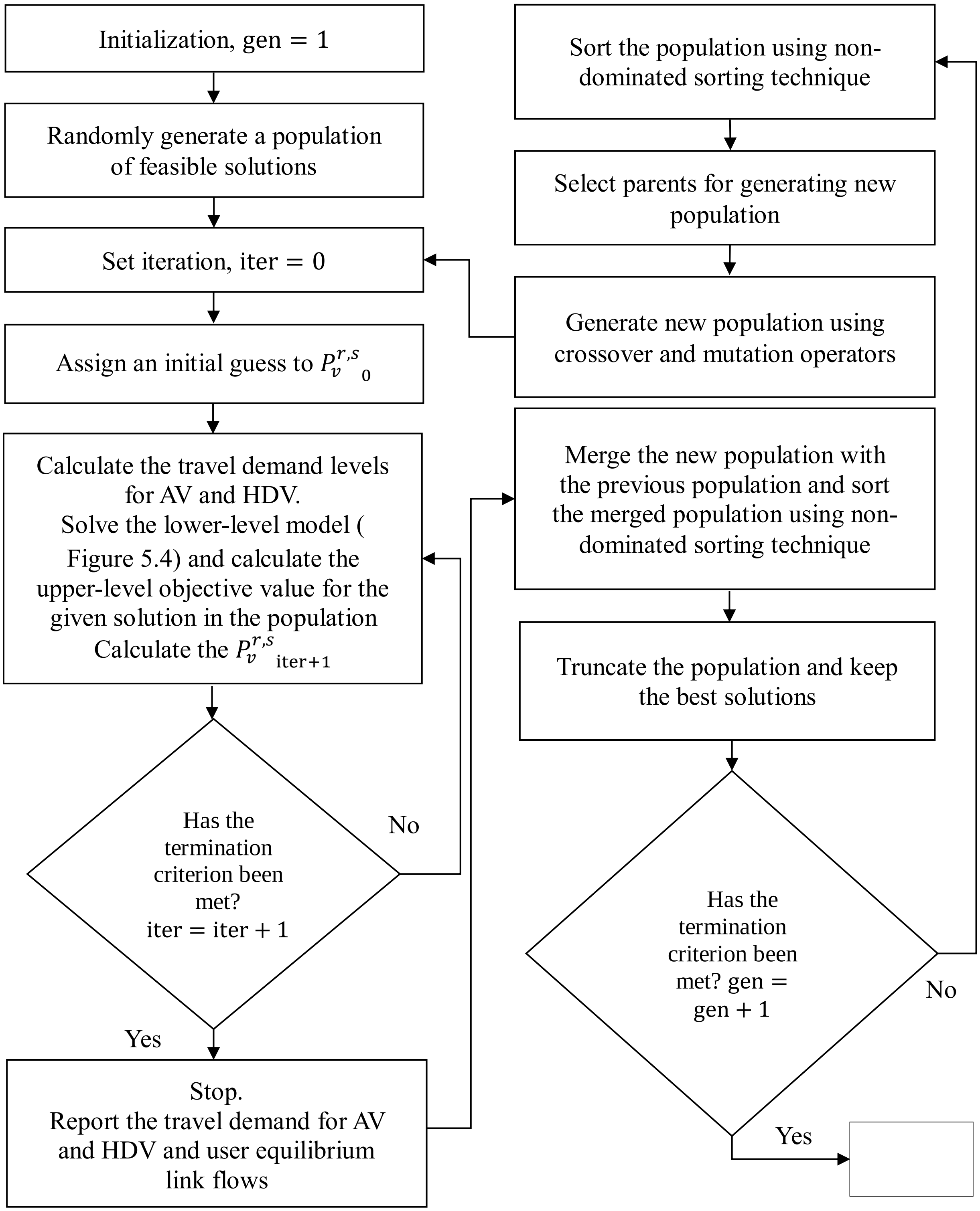


Figure 5.2 Algorithm flowchart

5.3 Solution Approach for the Lower-Level Model

Given charging facility locations and operating capacities from the upper level, the lower-level model can be solved. At the lower level, travelers' decision variables are the vehicle type (AV vs. HDV) choice and route choice. Travelers' vehicle type choice behavior model is solved using the fixed-point method. For travelers' route choice behavior, the Franke-Wolfe algorithm (1956) is used to solve the user equilibrium model. In the following sections, the solution approach for vehicle type and route choices of travelers is discussed in detail.

5.3.1 Vehicle Type (AV vs. HDV) Choice Solution Approach

The travelers' vehicle type choice between AV and HDV is related to the charging facility's location and capacity derived from the upper level and the user equilibrium travel times. In a subsequent section of this chapter, the UE solution method is explained. This section seeks to predict the travel demand for AV and HDV users, considering the charging facility locations, and the users' route choice behavior. The method of fixed-point iteration is used in this section to capture travelers' vehicle type choice. The basic principle of this method is to convert the equations into the form $\mathrm{x} = \mathrm{f}(\mathrm{x})$ and then to use the iterative scheme ($\mathrm{x}_{\mathrm{iter}+1} = \mathrm{f}(\mathrm{x}_{\mathrm{iter}})$) with an initialization of x_0. Repeat this process until the stopping condition is satisfied. The AV and HDV user demand, levels are treated as the fixed point (x) in this problem, while the user equilibrium is treated as the function (f(x)). The procedure for the fixed-point iteration method for the selection of AV and HDV is described in detail, as follows:

Step 1: The algorithm sets iteration, $\mathrm{iter} = 0$, and starts with initialization of ${P_v^{r,s}}_0$ regarding the probability of using AV and HDV.

Step 2: In this step, the travel demand for AV and HDV users is calculated by placing ${P_v^{r,s}}_{\mathrm{iter}}$ in equation (4.11). Based on the calculated travel demand for AV and HDV, the user equilibrium model can be solved. Then, by substituting the minimum travel time of AV/HDV users traveling from origin r to destination s derived from the UE into Equation (4.9), the probability of choosing AV/HDV (${P_v^{r,s}}_{\mathrm{iter}+1}$) can be derived from Equation (4.10).

Step 3: The algorithm checks the convergence of $d_v^{r,s}$, if the gap between ${d_v^{r,s}}_{\mathrm{iter}}$ and ${d_v^{r,s}}_{\mathrm{iter}+1}$ is less than some tolerance limit, epsilon (ϵ), then the algorithm stops, otherwise, it returns to step 2. Based on the current demand for AV and HDV, the user equilibrium link flows and the value of the upper-level objective can be calculated.

5.3.2 User Equilibrium Solution Approach

Travelers' route choice is related to the charging facility locations and capacities derived from the upper level and the AV/HDV travel demand calculated in Section 5.3.1. In this section, UE model is solved using the Franke-Wolfe algorithm (1956). In each step of the Frank-Wolfe algorithm, a shortest path algorithm needs to be solved in a way that the shortest path generated ensures the feasibility of the path in terms of EV charging needs. A shortest path algorithm proposed by Bahrami et al. (2017) is used in this study to ensure the path feasibility. In the sections that follow, first, Bahrami's algorithm is discussed in detail, and then, the Frank-Wolfe algorithm is described in a step-by-step manner.

5.3.3 Constrained Shortest Path (CSP) Algorithm

Bahrami et al. (2017) developed a Constrained Shortest Path (CSP) algorithm by modifying Bellman's algorithm (1958) to address the EV shortest path problem. Unlike Bellman's algorithm, which records the path and the corresponding travel time from origin to the node, the CSP algorithm keeps all feasible non-dominated paths and the corresponding travel time ($\eta_i^{r,s,v}$) and vehicle battery range ($b_i^{r,s,v}$) from origin r to node i using EV type v. Bellman's algorithm solves the shortest path problem based only on travel time; therefore, it is referred to as a "single-label" algorithm. On the other hand, the CSP algorithm solves the shortest path problem based on both the travel time and the battery range of the vehicle and is referred to as a "multi-label" algorithm. To determine the shortest path, the CSP algorithm uses the non-dominated sorting technique and stores all feasible non-dominated paths. In addition, in Bellman's algorithm, a number of sub-paths are included in the optimum shortest path from a given origin to a given destination, where each sub-path connects the origin node to the nodes visited along the path. Bellman's optimality theory states that all sub-paths within a path are optimal in themselves. However, this theory does not apply to the shortest path for EVs. Bahrami et al. (2017) stated that their modification ensures that the shortest path generated is feasible and optimal.

As shown in the algorithm pseudocode (Figure 5.3), the CSP algorithm initializes the algorithm by creating a path list for each node. Each row of the path list consists of the path, travel cost, and vehicles battery range from origin to the node. The CSP algorithm enumerates all feasible paths from origin r to other nodes in the network and stores non-dominated paths based on the travel time and vehicle battery range, then the algorithm selects the optimum shortest path based on travel time in the path list for each node.

Step 1: Create a path-list for each node. Set $\eta_i^{r,s,v} = \infty$ $(i \in N - \{r\})$, $\eta_r^{r,s,v} = 0$, $b_i^{r,s,v} = 0$ $(i \in N - \{r\})$, $b_r^{r,s,v} = \bar{R}$, and $\text{iter} = 1$.

Step 2: **while** $\text{iter} \leq |N| - 1$:

for all links $(i, j) \in A$:

$\bar{\eta}_j^{r,s,v} = \eta_i^{r,s,v} + t_{i,j}$

if $\left(\mathrm{z_{ij}} + \mathrm{y_{ij}}\right) > 0$

$\bar{b}_j^{r,s,v} = b_i^{r,s,v} - \mathrm{L_{ij}} + \mathrm{r_{ij}}$

else

$\bar{b}_j^{r,s,v} = b_i^{r,s,v} - \mathrm{L_{ij}}$

end

for each path p of path list of node i:

if $\bar{b}_j^{r,s,v} \geq 0$:

for each path p' of path list of node j:

if $\left[\eta_j^{r,s,v}, b_j^{r,s,v}\right]$ dominates $\left[\bar{\eta}_j^{r,s,v}, \bar{b}_j^{r,s,v}\right]$:

do nothing.

else:

add $[\{p, i\}, \bar{\eta}_j^{r,s,v}, \bar{b}_j^{r,s,v}]$ to the path list of j.

end

end

end

end

end

$\text{iter} = \text{iter} + 1$.

end

Step 3: **for** all nodes $(i \in N)$: sort the path list based on the $\eta_i^{r,s,v}$ and return the path with minimum travel cost as the shortest path.

end

Figure 5.3 Constrained shortest path (CSP) algorithm pseudocode

5.3.3 Frank-Wolfe Algorithm Solution Approach

The user equilibrium model is solved using the Frank-Wolfe algorithm, which is a well-known method for solving traffic assignment problems. Figure 5.4 illustrates the UE solution approach flowchart, and the rest of this section describes the algorithm in a step-by-step manner.

Step 0: Algorithm starts setting $\text{iter} = 0$ and solves the CSP algorithm to determine the shortest paths between all origins and destinations for each type of vehicle, based on the free-flow travel times $t_{0,i,j}$. Then it assigns travel demand of each O-D pair to the generated shortest path.

Step 1: In this step, the algorithm sets $\text{iter} = \text{iter} + 1$, updates the link travel times, and assigns all travel demand on the shortest path, to obtain the feasible direction of link flows α_{iter}.

Step 2: The algorithm calculates link flow ${x_{i,j}}_{\text{iter}+1} = \alpha_{\text{iter}} {x_{i,j}}_{\text{iter}} + (1 - \alpha_{\text{iter}}) {x_{i,j}}_{\text{iter}-1}$ for each link.

Step 3: The algorithm checks the convergence of $x_{i,j}$, if the gap between ${x_{i,j}}_{\text{iter}}$ and ${x_{i,j}}_{\text{iter}+1}$ is less than some tolerance limit, say epsilon (ϵ) the algorithm stops. Otherwise, go to Step 1.

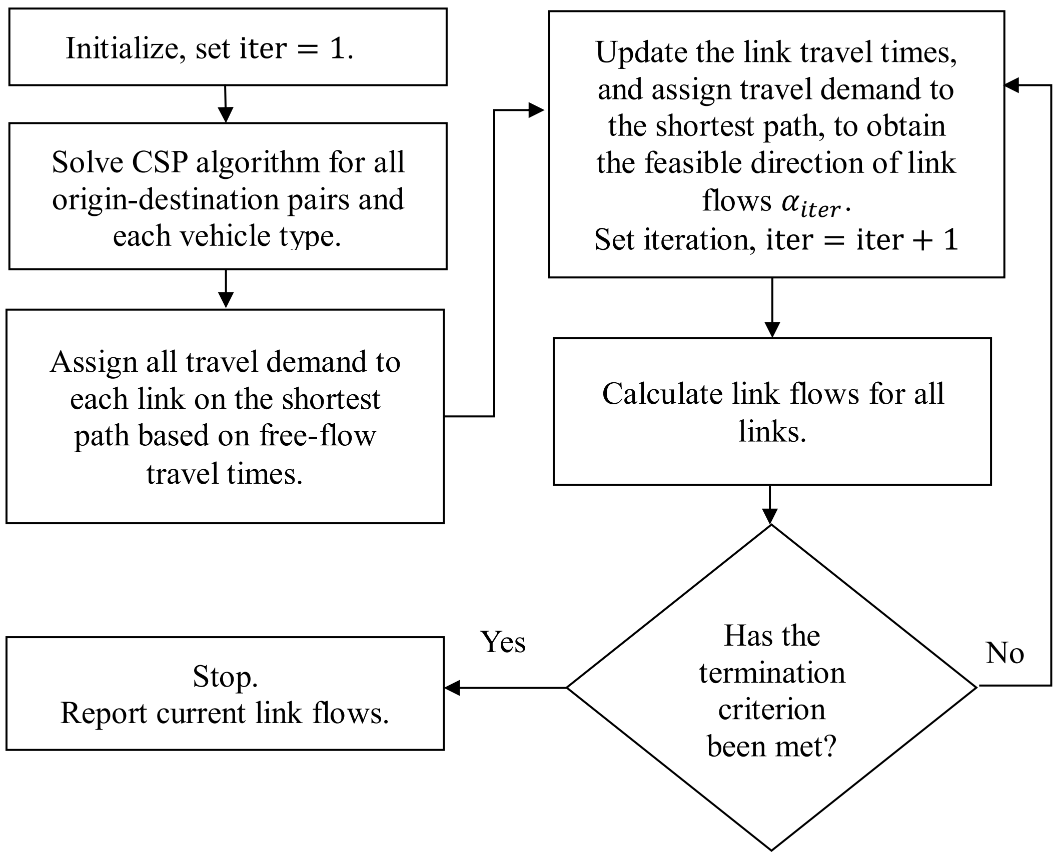


Figure 5.4 Lower-level solution flowchart

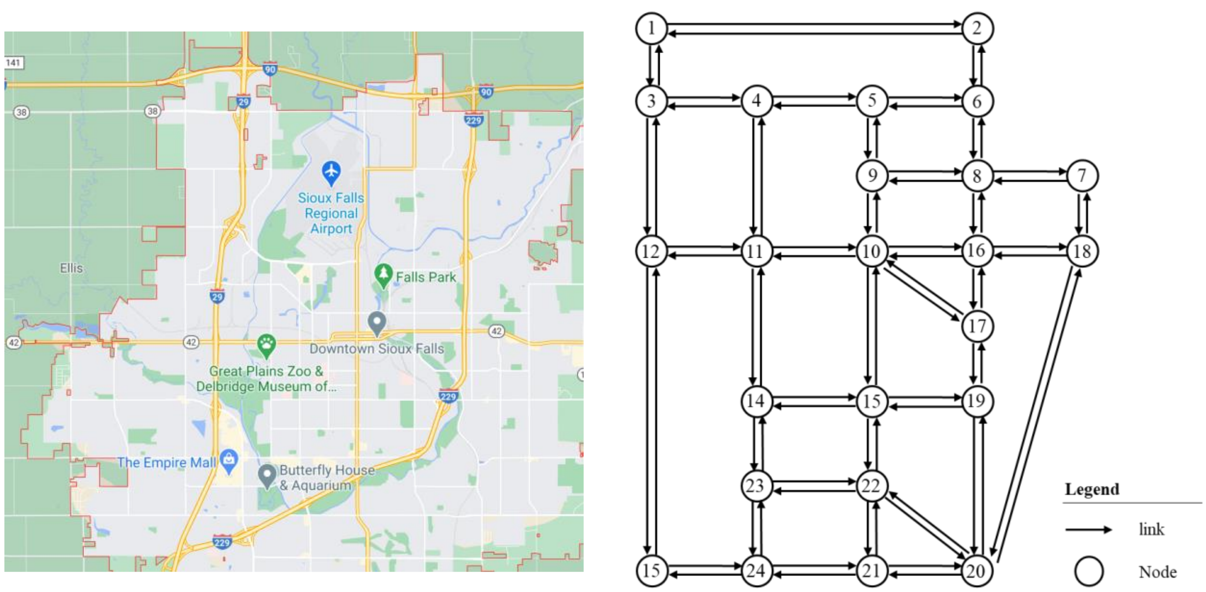
5.4 Summary of the Chapter

This chapter discusses the solution approach for each level. In order to solve the proposed bi-level model, a population of viable solutions was generated at the upper level. For each solution, at the lower level, the travel demand for AV and HDV users was determined by solving the logit model using the solution algorithm (from Section 5.3.1). Then, the user equilibrium link flows were calculated using Frank-Wolfe algorithm presented in Section 5.3.2. In each step of the Frank-Wolfe algorithm, a shortest path algorithm proposed by Bahrami et al. (2017) is solved in a way that the shortest path generated ensures the feasibility of the path in terms of EV charging needs. At the upper level, objective values were calculated. Based on the objective value of each solution, parents were chosen to generate a new population. The new population was generated by crossover and mutation operators. The new population was merged with the previous population and sorted by non-dominated sorting techniques, and the best solutions were left for the next iteration. This iterative scheme was repeated until the stopping criterion had been met.

CHAPTER 6 NUMERICAL EXPERIMENTS

6.1 Introduction

In this chapter, numerical experiments are carried out to demonstrate the applicability of the proposed model. This chapter tests the proposed bi-level model using the Sioux-Falls road network. The Sioux Falls, North Dakota, road network (Figure 6.1) has 24 nodes and 76 links. The network characteristics and travel demand can be found in Leblanc et al. (1975). Although the Sioux-Falls network is small, it is a well-known network that is used in network design problems (Hosseininasab et al., 2018; Miralinaghi et al., 2020; Wang et al., 2016). Furthermore, the framework proposed in this study is applicable to larger networks. The solution algorithm is coded in MATLAB 2020. A Core i7 processor with a 2.6 GHz CPU and 8 GB RAM is used to obtain the results. This chapter first presents the computational settings. Then, the obtained Pareto-optimal solutions for the case study are presented in detail. Sensitivity analysis is then carried out in order to understand the impact of following factors on the planning of charging facilities: agency-user cost weight ratio, EV charging investment budget, multiplicity of EV charging facility type, lane type, EV driving range, and AV purchase price.



(a)Sioux Falls, North Dakota (b) The Sioux Fall road network

Figure 6.1 The road network of Sioux-Falls, North Dakota

6.2 Computational Setting

As shown in Figure 6.2, the Sioux Falls road network has been associated with fourteen (14) potential AV-exclusive lanes (Chen et al., 2016), (see red arcs in Figure 6.2). We have considered similar locations for the AV-exclusive lanes as Chen et al. (2019) had proposed. According to Tientrakool et al. (2011), the capacities of AV-exclusive lanes are assumed to be 43% greater than that of general-purpose lanes at the same link. This is because the capability of AVs enables them to move at reduced headways and consequently, increases the road capacity. In Figure 6.2, nodes shown with broken circles indicate specified candidate nodes for constructing charging stations, and broken arrows indicate specified candidate links to install wireless-charging facilities in the outskirts of the Sioux-Falls road network.

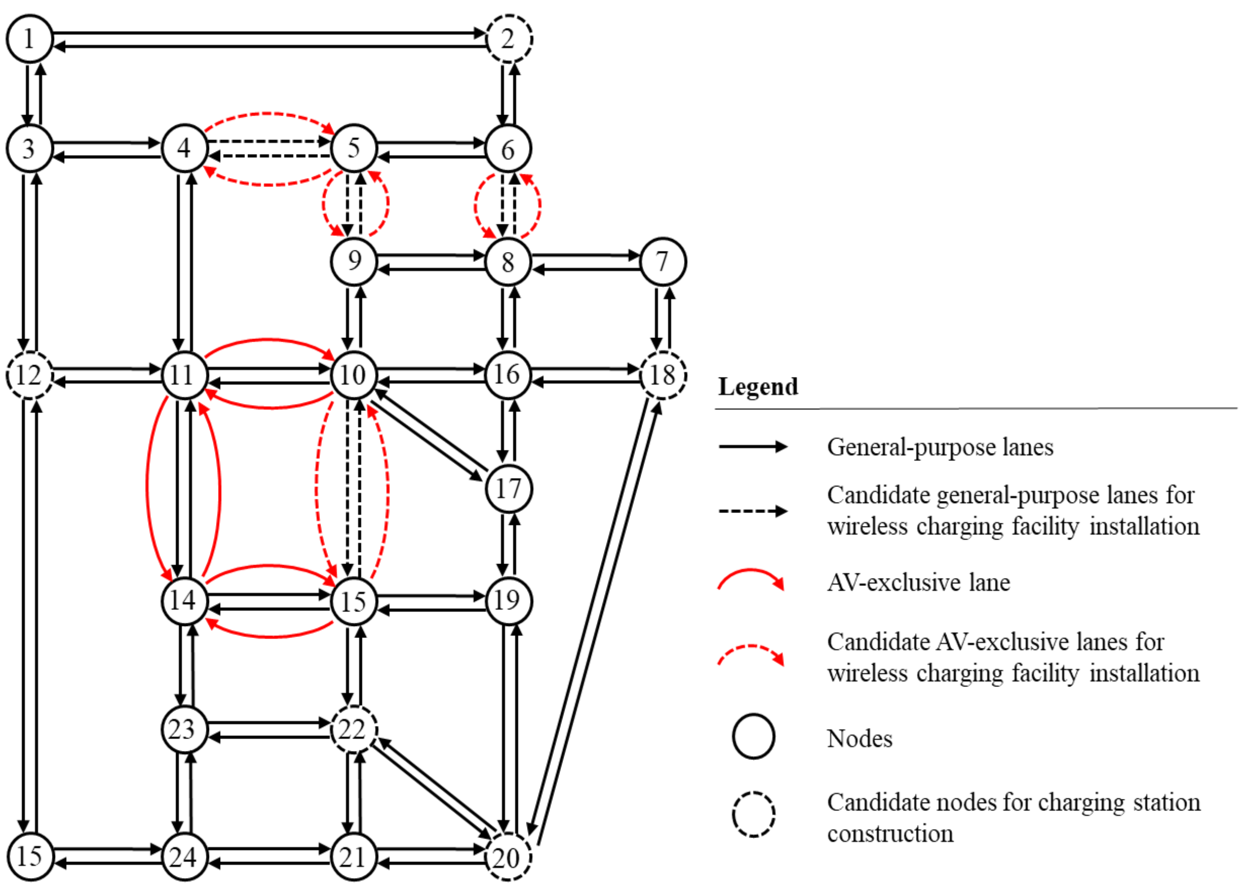


Figure 6.2 Sioux-Falls road network with candidate nodes and links for EV charging facilities

The analysis also included assumed values of the charging facility capacities and construction costs. It is assumed that the transportation decision-makers consider two different capacity levels for the charging station. In addition, the given capacity of the level 1 charging station is set as 300 veh/hr. The construction cost factors for charging stations are $200,000 and $800,000 dollars, respectively (Smith & Castellano, 2015). Therefore, the charging station construction cost can be calculated using Equation (4.2). In other words, the construction cost of levels 1 and 2 charging stations with capacities of 300 and 600 veh/hr are $1 million and $1.8 million, respectively (Table 6.1).

Table 6.1 Cost of constructing charging stations at candidate nodes.

Charging station capacity level	Capacity	Construction Cost ($M)
1	300	1
2	600	1.8

Table 6.2 Cost of installing wireless-charging lanes at candidate links.

Candidate link	Length (mile)	Construction cost ($M)
(4,5)	2	8
(5,4)	2	8
(6,8)	2	8
(8,6)	2	8
(5,9)	5	20
(9,5)	5	20
(10,15)	6	24
(15,10)	6	24

According to Fuller et al. (2016), the average annual cost of development (installation, operations, and maintenance) of a wireless-charging facility is $4 million per mile per lane. Based on this, the average cost of installing wireless-charging facility on the candidate links of the case study network can be calculated using equation (4.3), and results are provided in Table 6.2. In the base analysis, based on the EV charging facility development costs, the budget for constructing charging facilities (B) is estimated to be $40 million. Sensitivity analysis is then carried out in order to understand the impact of EV charging facility investment budget levels in Section 6.6. It is assumed that the average initial (pre-trip) battery range of EVs is 15 miles. The VOT for HDV users is assumed to be equal to $20 per hour (FHWA, 2016). According to Correia et al. (2019), compared to HDV users, the VOT is almost 25% less for AV users (level 3 and higher). Hence, the VOT for AV users is assumed to be equal to $15 per hour. The weights of travel time and purchase price of the vehicle in the utility function (Equation (4.9)) are set as -0.0375 and -1, respectively, based on the suggested weights by Nie et al. (2016). Similar to the values used by Liu et al. (2017), the average annual income of travelers is assumed to be $80,000, the average purchase price of AV and HDV are set as $40,000 and $20,000, respectively, and the average life expectancy of vehicles is assumed to be ten years. All costs are in 2020 US dollars. Also, the analysis period is only the first year of implementation, therefore the discount rate is not considered. In the rest of this chapter, the terms "development" and "construction" are used synonymously.

6.3 Base Analysis

The Pareto frontier obtained using the NSGA-II algorithm for the case study is illustrated in Figure 6.3. For the Pareto Optimal (PO) solution "A", only one level 1 charging station is selected for construction, and this is at node 18, also one lane is selected for wireless-charging construction, and this is at the general-purpose lane (4,5), as shown in Figure 6.4(a). For the PO solution "B", one general-purpose lane (5,4) and also, one AV-exclusive lane (6,8) are selected for wireless-charging facility construction, and one level 1 charging station (at node 18) is selected for construction, as shown in Figure 6.4(b). For the PO solution "C", two general-purpose lanes (4,5) and (5,4) and one AV-exclusive lane (6,8) are selected for wireless-charging facility construction, and one level 1 charging station (at node 18) is selected for construction, as shown in Figure 6.4(c). For the PO solution "D", three general-purpose lanes (4,5), (5,4), and (6,8), one AV-exclusive lane (8,6) are selected for wireless-charging facility construction and one level 2 charging station (at node 18) is selected for construction, as shown in Figure 6.4(d). Table 6.3 summarizes the PO solutions obtained for the case study.

Figure 6.5 illustrates the convergence of the upper-level objective function over the iterations for the case study. As can be seen in this figure, the algorithm converges after 35 iterations. The average and maximum computation time for each run of the algorithm for this case study are 23.5 and 26.3 minutes, respectively.

Table 6.3 Pareto-optimal solutions for EV charging facility locations, construction cost, and travelers' total travel time cost

Pareto Optimal Solution	Charging station locations and capacities	Wireless charging facility locations	Total Travel Time Cost ($M)	Construction Cost ($M)
A	Level 1 at node 18	One general-purpose lane (4,5)	16.9	9
B	Level 1 at node 18	One general-purpose lane (5,4), one AV-exclusive link (4,5)	7.9	17
C	Level 1 at node 18	Two general-purpose lanes (4,5) and (5,4), one AV-exclusive link (6,8)	6.5	25
D	Level 2 at node 18	Three general-purpose lanes (4,5), (5,4), and (6,8), one AV-exclusive link (8,6)	5.6	33.8

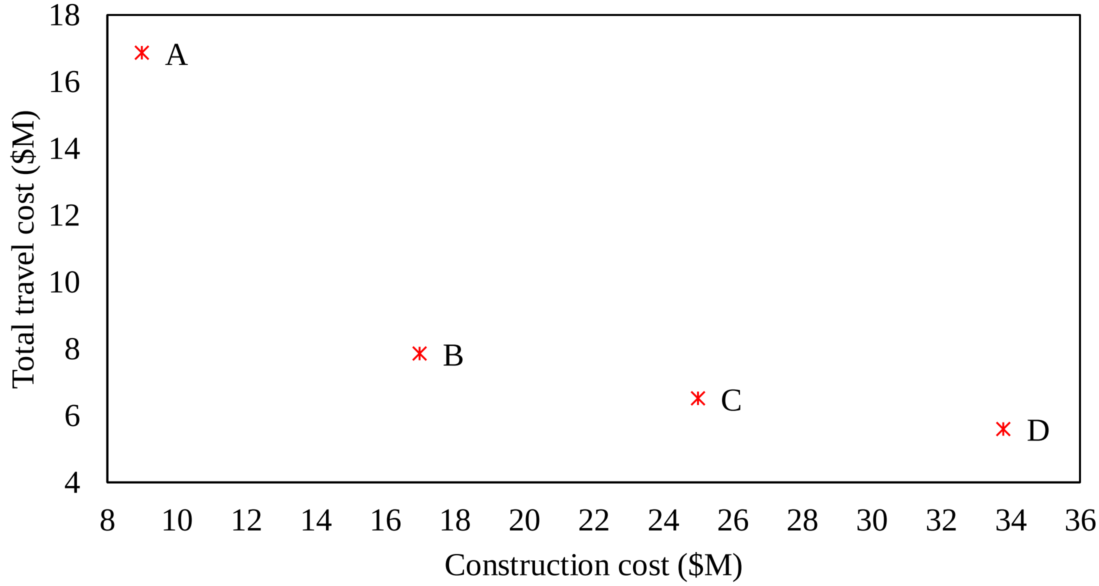
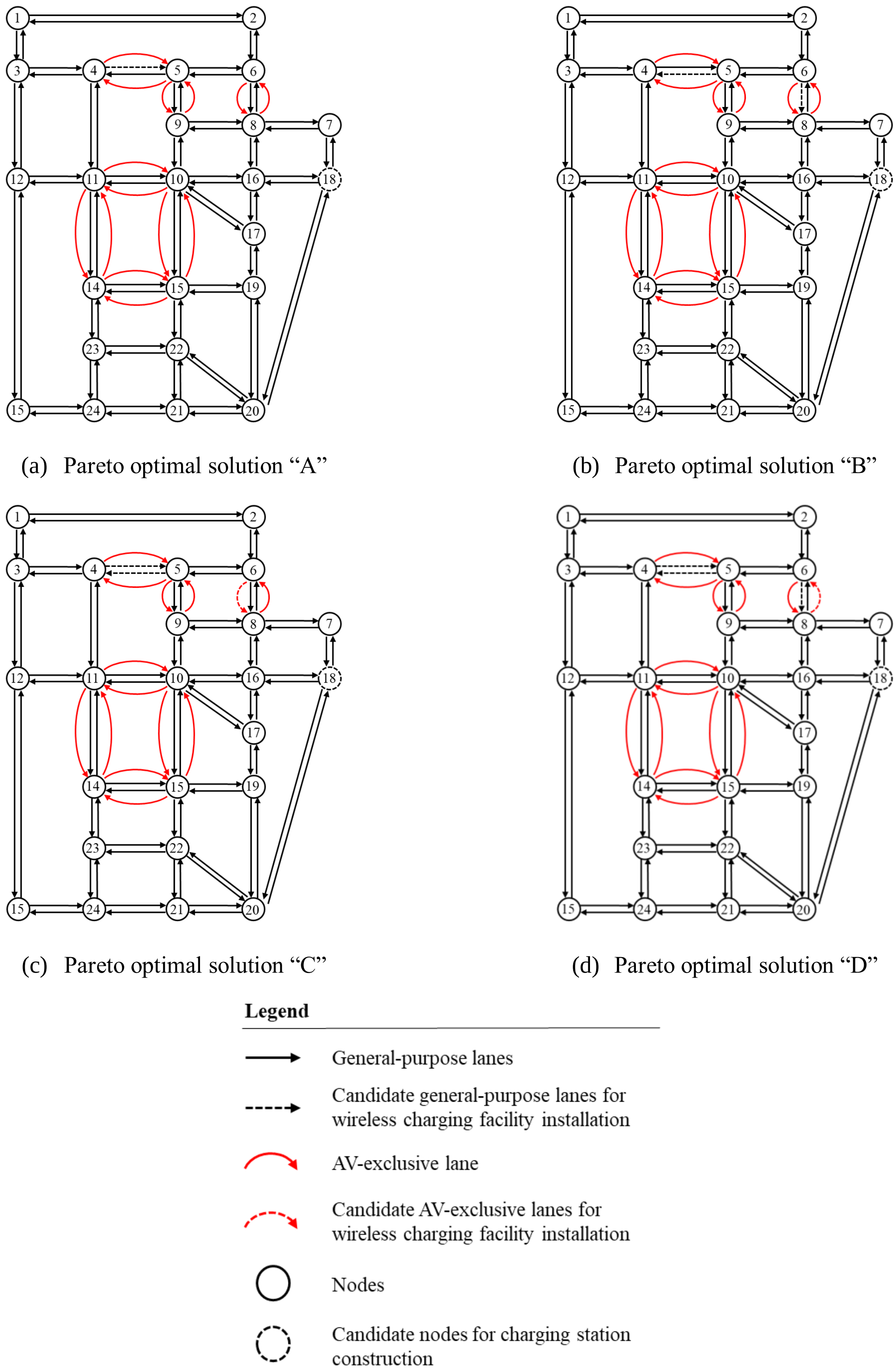


Figure 6.3. Pareto optimal solutions for the case study



(a) Pareto optimal solution “A”

(b) Pareto optimal solution “B”

(c) Pareto optimal solution “C”

(d) Pareto optimal solution “D”

Figure 6.4. Pareto-optimal solutions for EV charging facility location, Sioux Falls road network

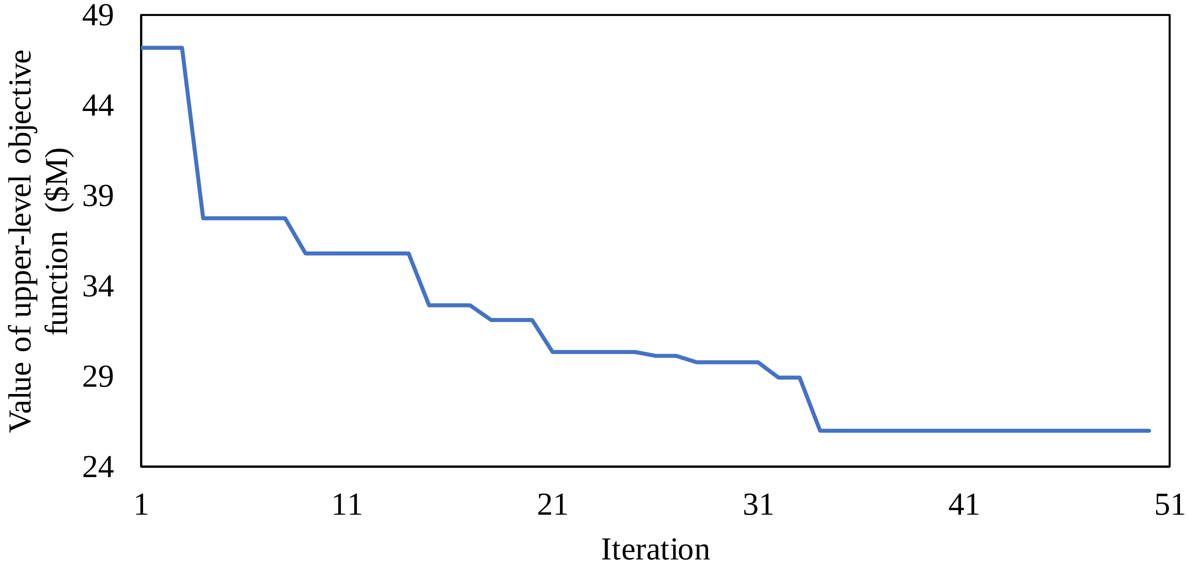


Figure 6.5. Convergence of the upper-level objective function over the iterations

6.4 Tradeoffs between Asset Investment Levels and Asset Levels of Service

In transportation asset management, the decision-makers often encounter a need to quantify the tradeoffs between asset investment levels (incurred by the agency) and asset levels of service (enjoyed by the users) (Bai et al., 2008; Bai et al., 2012). In the context of this chapter, the tradeoffs involve EV charging facility construction and user costs of total travel time. For example, if few EV charging facilities are constructed, this will cause EV user delay and higher travel time costs and, consequently, user dissatisfaction. If too many charging facilities are constructed, this will lead to excess idle time and, consequently, waste of investment resources. Therefore, a good balance should be achieved between agency savings and user benefits.

According to the PO solutions obtained for the case study, the total travel time cost decreases as the construction cost increases across PO solutions “A,” “B,” “C” and “D”. This indicates, intuitively, that the transportation decision-makers can reduce total travel time costs significantly by increasing the EV charging facility investment. Hence, if the transportation agency considers the costs of travelers to be significantly important, then the strategy of PO solution “D” will be chosen. On the other hand, the relatively higher emphasis on the construction cost leads to the selection of the PO solution “A” in which fewer number of EV charging facilities will be constructed, and the fewer number of charging facilities will result in higher total travel time costs.

It is clear that with increasing EV charging facility investment the number of EV charging facilities increases, and consequently, charging delay decreases. Interestingly, with increasing the EV charging facility investment, the model decides to install more wireless-charging facilities rather than charging stations. This is because wireless-charging facilities have significantly lower charging delay compared to charging stations.

6.5 Sensitivity Analysis on the Weights of Construction Cost and Total Travel Time Cost

In making decisions based on multiple criteria, the transportation decision-maker often encounters the need to assign relative weights to each performance objective or metric to reflect its relative importance compared to other objectives or metrics (Patidar et al., 2007; Sinha et al., 2009), for example, to what extent is the network investment cost savings more important than user delay reduction? The methods often used to establish the weights include equal weighting, regression-based observer-derived weighting, direct weighting, gamble method, analytical hierarchy process (AHP), and value swinging, and these are described in the literature (Hobbs & Meier, 2000; Sinha & Labi, 2007). In this chapter, the direct-weighting method was used. The relative weights may change from time to time and across locations to reflect different circumstances and policies of the highway system owner (Labi, 2014). As such, it is often useful to assess the sensitivity of the optimal solution to changes in weights (Hobbs & Meier, 2000). To analyze the sensitivity of the optimal solution to the relative importance between the agency dollar and the user dollar, the objective of the upper-level was formulated as a weighted sum of objectives by assigning weights to the travel time cost and construction cost, to reflect the importance of each criterion, as follows:

$$Z^U = \min[(1-\xi)\phi_1 + \xi \cdot \phi_2] \tag{35}$$

$$0 \leq \xi \leq 1 \tag{36}$$

where ξ denotes the weight of construction cost relative to the user cost. Figure 6.6 illustrates the impacts of changes in agency-user cost weight ratio (ξ) on the total travel time costs and construction costs. With $0 \leq \xi \leq 0.1$ the transportation decision-makers consider user costs to be of significantly important; and the strategy of PO solution “D” will be chosen. With increasing the importance of the agency (construction) cost relative to the user cost, the PO solution “C” and “B” will be chosen for $0.2 \leq \xi \leq 0.3$ and $0.4 \leq \xi \leq 0.7$, respectively. A higher importance attached to the agency cost dollar relative to the user cost dollar, that is, $0.8 \leq \xi \leq 1$. This yields to PO solution “A”.

Based on the weights provided by Lamptey et al. (2005) and Patidar et al. (2007), the remaining analysis in this chapter is conducted using 0.65 and 0.35 as the weights for the agency and user costs, respectively, that is, $\xi = 0.65$.

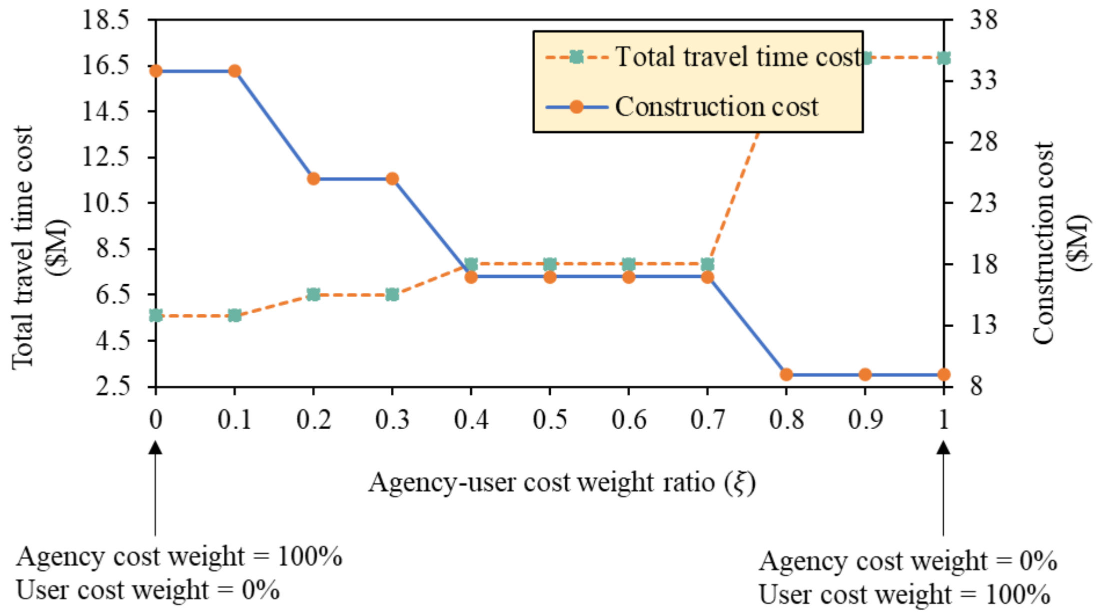


Figure 6.6 Impacts of different agency/user relative weights the optimal total travel time and construction costs

6.6 Sensitivity of the Optimal Solution to the EV Charging Construction Budget

In this set of analyses, we seek to investigate the impact of the EV charging investment budget on the optimal solution. Table 6.4 presents the three scenarios (levels) of the construction budget and Table 6.5 presents the results.

Table 6.4. Different construction budget levels (in million dollars)

Budget scenario	Construction budget ($M)
Scenario 1	10.00
Scenario 2	20.00
Scenario 3	40.00

The outcomes of these scenarios are compared with a base scenario (referred to as scenario 0). In Scenario 0, it is assumed that the EV driving range is very high and therefore there is no need for intra-trip recharging, and therefore does not require construction of charging facilities in the network. In this scenario's result (optimal solution), the total travel time cost for EVs is $5.65 million, and the AV market penetration is equal to 49.8 percent. High EV driving range leads to lower travel time costs for both AV and HDV users because they experience lower recharging delay at charging facilities. In addition, with a reduction in travel time costs, AV market penetration decreases due to higher purchase price compared to HDV. In the rest of this chapter, the results of each scenario are compared with those of Scenario 0.

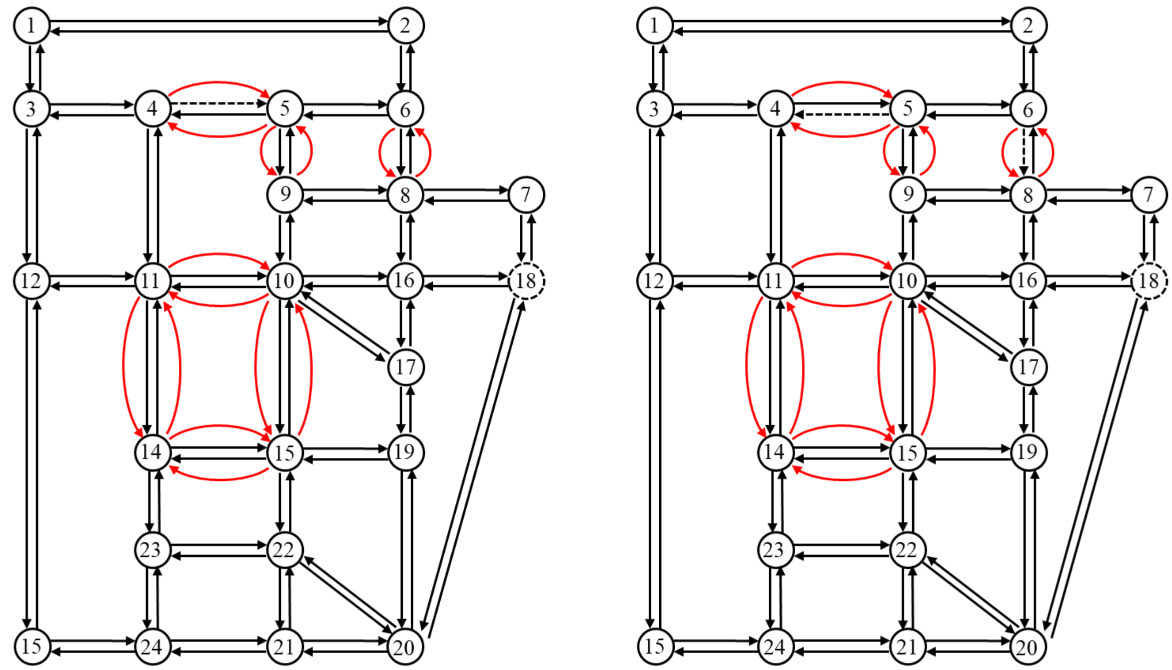
As shown in Table 6.5, the total cost, which is unweighted sum of construction and travel time costs, reduces as the level of EV charging facility investment (construction budget) increases. This is anticipated theoretically as an increase in the construction budget (B), i.e., the right-hand side of the equation (4.5) in the upper-level model, leads to an expansion of the feasible region, and consequently, identification of superior solutions. When budget is given at a low level of $10 million which is referred to as "Scenario 1" (Figure 6.7(a)), the solution prescribes construction of a level 1 charging station at node 18 and installation of a wireless-charging facility at general-purpose lane (4,5). In this scenario, compared to Scenario 0, the total travel time cost increases by $9.1 million. This additional cost is attributed to charging delay at the charging stations and the added travel time because vehicles deviate from their optimal routes in order to recharge.

When the budget is $20 million (Scenario 2), the obtained solution (Figure 6.7(b)), prescribes construction of a level 1 charging station at node 18 and installation of a wireless-charging facilities at two general-purpose lanes (5, 4) and (6, 8). In this scenario, by providing more charging facilities, charging delay, and added travel time cost (which are due to the EVs deviation from their respective optimal routes to recharge) decreases. In Scenario 3, when the budget is $40 million (Figure 6.8), and the optimal solution prescribes construction of a level 1 charging station at node 18 and installation of wireless-charging facilities at two general-purpose lanes (4, 5), (5, 4), and one AV-exclusive lane (6, 8). The total travel time cost is very close to that of Scenario 0. This is because a higher budget scenario has led to more charging facilities in the network and, consequently, lower recharging delays and lower added travel times caused by deviating from optimal routes to recharge.

It is observed from the results that the model prioritizes the construction of wireless-charging facilities over charging stations. This is intuitive because road users are expected to prefer recharging at wireless-charging lanes to avoid the extra recharging delay associated with charging stations. The results show the extent to which increased levels of EV charging facility investment (construction budget) translate into charging delay reduction and subsequent reduction in travel time relative to recharging at stations. This trade-off is useful for consideration by the policy makers. It is critical that transport agencies are aware of the sensitivity of the recommended EV charging facility locations to the key factors of the analysis. Such knowledge will help them decide, at the planning stage, the appropriate investment budget levels for this infrastructure.

Table 6.5 Numerical results for different construction budget levels ($M)

Budget scenario	Construction budget	Construction cost	Total travel time cost	Total cost (unweighted sum)
Scenario 0	0.00	0.00	5.65	5.65
Scenario 1	10.00	9.00	14.75	23.75
Scenario 2	20.00	17.00	9.95	26.95
Scenario 3	40.00	25.00	5.72	30.72



(a) Scenario 1 (budget = $10 million)

(b) Scenario 2 (budget = $20 million)

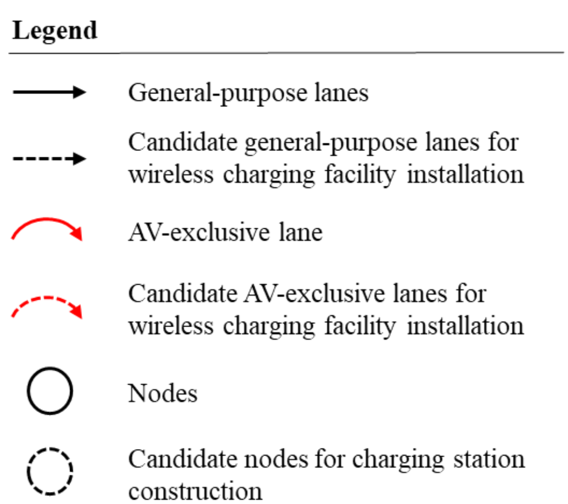
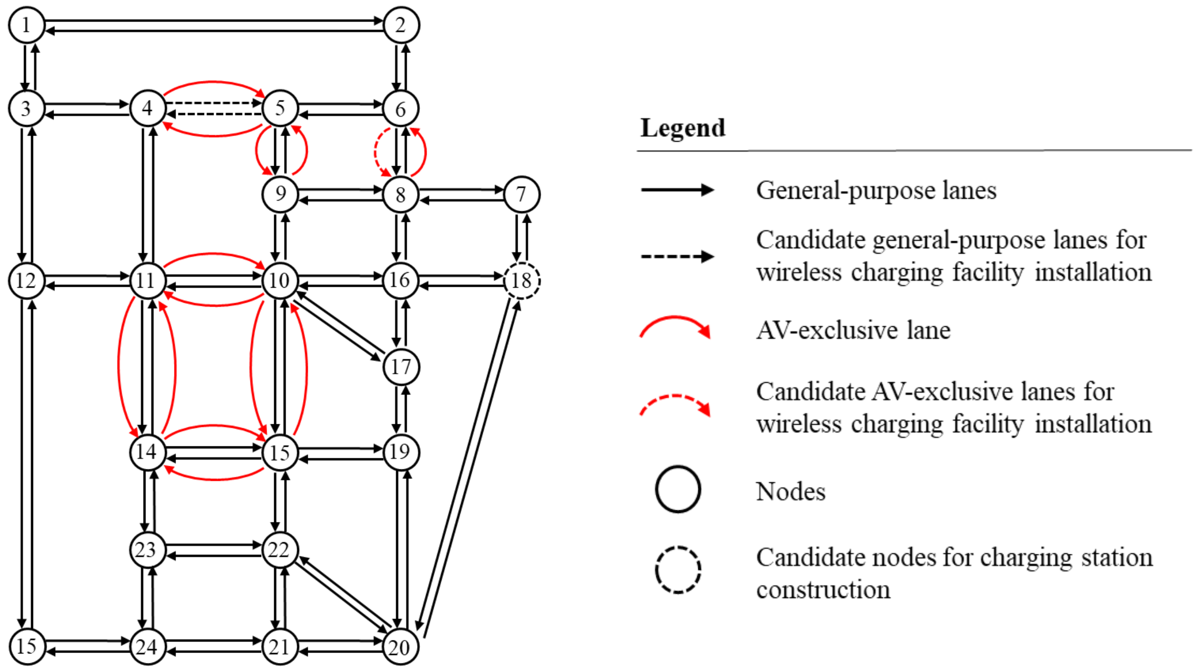


Figure 6.7 Optimal locations for new charging facilities, $10-20M investment budget



Scenario 3 (budget = $40 million)

Figure 6.8 Optimal locations for new charging facilities, $40M investment

Interestingly, it is observed that AV market share decreases slightly as the construction budget increases from Scenario 1 to Scenario 2 (as seen in Figure 6.9). Then, there is an observed increase in the AV market share from Scenario 2 to Scenario 3. The initial decrease is because, as the budget increases from $10 million to $20 million, the model prescribes installation of wireless-charging facilities on general-purpose lanes to satisfy both AV and HDV users' recharging needs. Although this reduces travel time for both AVs and HDVs, AV market penetration decreases because it depends on purchase price and travel time. The purchase price of AV is higher compared to purchase price of HDV; therefore, the market penetration rate of AVs decreases when wireless-charging facility is provided at general-purpose lanes. As the budget increases from $20 million to $40 million, the model prescribes installation of wireless-charging facilities at AV-exclusive lane (6, 8), leading to an increase in AV market penetration.

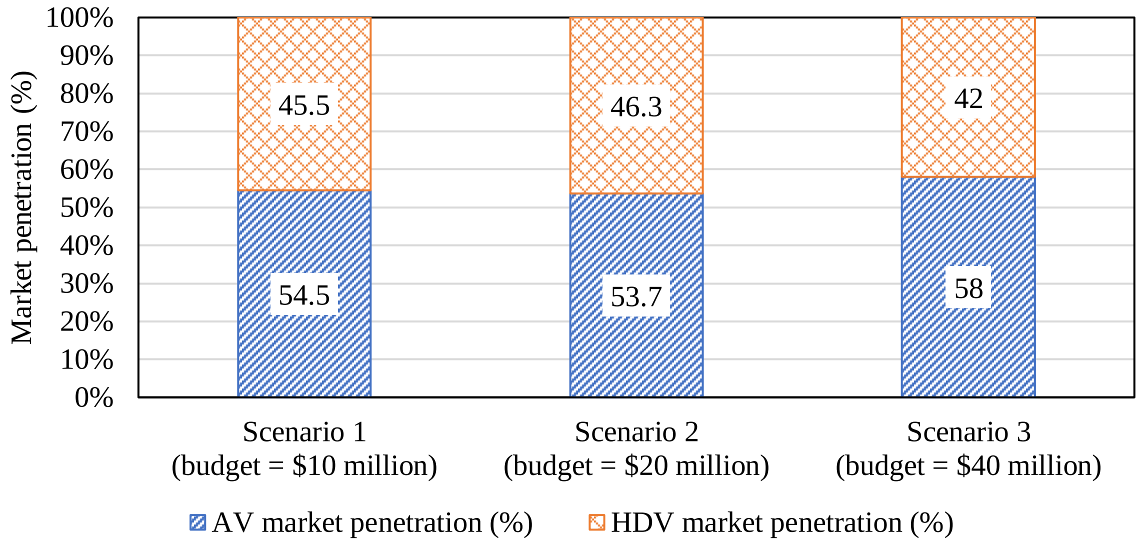


Figure 6.9 AV and HDV market penetration at different investment levels

6.7 Comparison with Result of Considering only one Method of EV Charging Facility

In this section, the impact of only one method of EV charging facility (static charging station vs. dynamic wireless charging facility) on the optimal locations and the associated costs are discussed. In Scenario 1, the transportation decision-makers intend to provide wireless-charging only. In scenario 2, the transportation decision-makers intend to provide charging stations only. In Scenario 3, the transportation decision-makers intend to provide both charging stations and wireless-charging facilities. Table 6.6 presents the charging method considered in each scenario.

Table 6.6 EV charging method scenarios

EV charging method scenarios	EV charging methods
Scenario 1	Wireless charging facility
Scenario 2	Charging station
Scenario 3	Wireless charging facility and static charging

Figure 6.10 presents a comparison of the results of the scenarios. Scenario 0 (presented in Figure 6.10) is the same as the Scenario 0 presented in Section 6.6. For scenario 1, the result (optimal strategy) is to construct wireless-charging facilities at links (4, 5), (5, 4), (8, 6), and (5, 9), as shown in Figure 6.11(a). In this scenario, all candidates selected for wireless-charging facility installation are located at general-purpose lanes. This result is intuitive because the solution addresses the recharging needs of HDV users as well as AV users. As explained above, this leads to lower AV market penetration (i.e., 50 percent) compared to Scenarios 2 and 3. The charging delay for wireless charging is lower compared to charging stations; therefore, the increased travel

time in this scenario compared to Scenario 0 is primarily due to additional travel time spent by EVs in deviating from their optimal routes to recharge.

For Scenario 2, the result (optimal strategy) is to construct three level 1 charging stations at nodes 12, 18, and 22 (Figure 6.11(b)). In this scenario, the charging delay for charging stations is very high and travelers deviate from their optimal route to recharge. Therefore, the AV and HDV travel times of this scenario are higher than that of Scenario 0. Although the AV market penetration (i.e., 57 percent) resulting from this scenario is higher than that from Scenario 0 (i.e., 49 percent), the total travel time cost has not improved. This might be because the charging delay in charging stations for both AVs and HDVs are equal. This implies that without wireless-charging facility deployment, particularly at AV-exclusive lane, the impacts of AV market share in the total travel time cost decreases.

For Scenario 3, as shown in Figure 6.11(c), the result (optimal solution) recommends construction of one level 1 charging station at node 18, two wireless-charging facilities at two general-purpose lanes (4, 5) and (5, 4), and one wireless-charging facilities at AV-exclusive lane (6, 8). In this scenario, compared to Scenarios 1 and 2, the total travel time cost is too close to that of Scenario 0. This is due to two reasons: (i) the use of wireless-charging facilities in the network, and (ii) higher market penetration of AVs (i.e., 58%). Interestingly, the total travel time cost of HDV users in Scenario 3 increases slightly compared to Scenario 1. This is because, in scenario 1, the model decides to install all wireless-charging facilities at general-purpose lanes, which leads to lower travel time cost for HDV users.

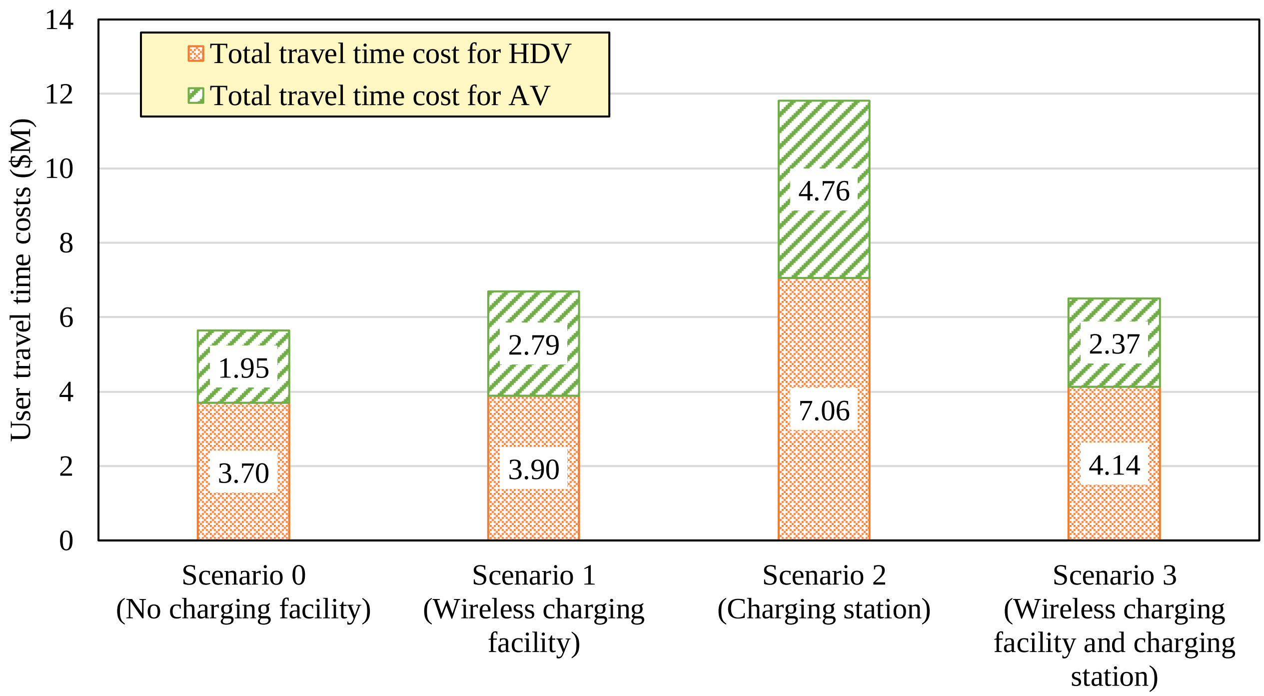
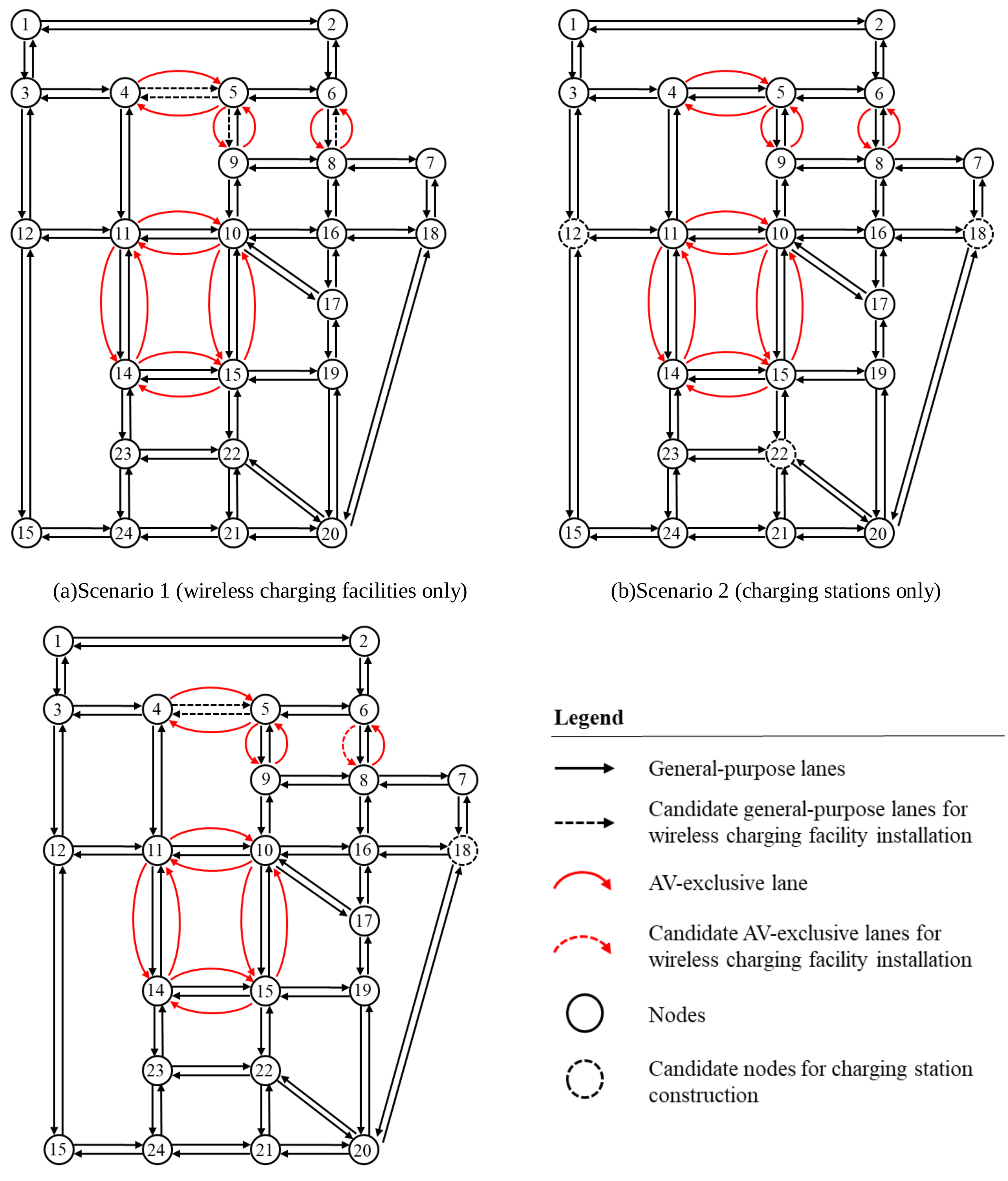


Figure 6.10 Total travel time costs under different scenarios



(a)Scenario 1 (wireless charging facilities only)

(b)Scenario 2 (charging stations only)

(c) Scenario 3 (wireless charging facilities + charging stations)

Figure 6.11 Optimal charging facility locations under different scenarios

6.8 Impacts of Selecting General-purpose vs. AV-exclusive Lanes for Wireless-charging Facility Installation

In this section, we investigate the impacts of selecting general-purpose and AV-exclusive lanes for wireless-charging facility installation on the optimal location and associated costs. Consider three scenarios. In scenario 1, the transportation decision-makers intend to install wireless-charging facilities only at AV-exclusive lanes. In Scenario 2, the transportation decision-makers seek to install wireless-charging facilities only at general-purpose lanes, and in Scenario 3, they seek to install wireless-charging facilities at either AV-exclusive or general-purpose lanes or both. Table 6.7 presents the lane type (AV-exclusive lane and/or general-purpose lane) that we considered for wireless charging facility installation for each scenario.

Table 6.7 Lane types for wireless charging facility installation scenarios

Scenario	Lane type
Scenario 1	AV-exclusive lane
Scenario 2	General-purpose lane
Scenario 3	General-purpose lane and AV-exclusive lane

Figure 6.12 compares the results of these scenarios. The base scenario (Scenario 0) presented here in Figure 12 is the same as the Scenario 0 presented in Section 6.6. For Scenario 1, the result (optimal strategy) is to construct one wireless-charging facility at AV-exclusive lane (5, 4) and three level 1 charging stations at nodes 12, 18, and 22 (Figure 6.13(a)). In this scenario, the model prescribes the construction of a greater number of charging stations compared to Scenarios 2 and 3, to meet the recharging needs of HDV users who cannot use the wireless-charging facilities at AV-exclusive lanes. Therefore, a higher number of charging stations, as discussed earlier in Section 6.7, results in higher total travel time cost compared to Scenarios 2 and 3. Specifically, the travel time cost for HDV users is observed to be significantly higher compared to scenarios 2 and 3. Again, this is because HDV users use charging stations and do not have a wireless charging option, leading to higher charging delays for them. Furthermore, this scenario could raise concerns related to social inequity due to the fact that the wireless-charging facilities are only provided for AV users.

For Scenario 2, the result (optimal strategy) is to construct wireless-charging facilities at two general-purpose lanes (4, 5), (5, 4), and a level 1 charging station at nodes 18 Figure 6.13(b). In this scenario, the total travel time cost is higher than that of Scenarios 1 and 3. This is because the provision of charging facilities only for general-purpose lanes leads to lower AV market penetration (i.e., 54 percent) and therefore higher travel time costs compared to those of scenario 1 and 3. Compared to Scenario 1, travel time cost for HDV users decreased slightly. This result

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seems intuitive because both charging stations and wireless-charging facilities are available for HDV users.

For Scenario 3, as shown in Figure 6.13(c), the result (optimal solution) prescribes one level 1 charging station at node 18 and installs two wireless-charging facility at two general-purpose lanes (4, 5) and (5, 4), and one wireless-charging facility at one AV-exclusive lane (6, 8). Compared to Scenario 1, the total travel time cost for AV users is slightly higher. This is because, unlike scenario 1, the model considers the availability of wireless-charging facilities for both AV and HDV users. In this scenario, the travel time cost is significantly lower compared to scenario 1 and 2. This result is due to (i) high investment in charging facilities, which result in lower recharging delays and added travel times (which is due to deviation from optimal routes to recharge), and (ii) high AV market penetration. Overall, the total travel time cost of this scenario is lower than those of scenarios 1 and 2 indicating that the provision of wireless-charging facilities for both AV and HDV users not only addresses the social equity concerns but also significantly reduces the total travel time cost.

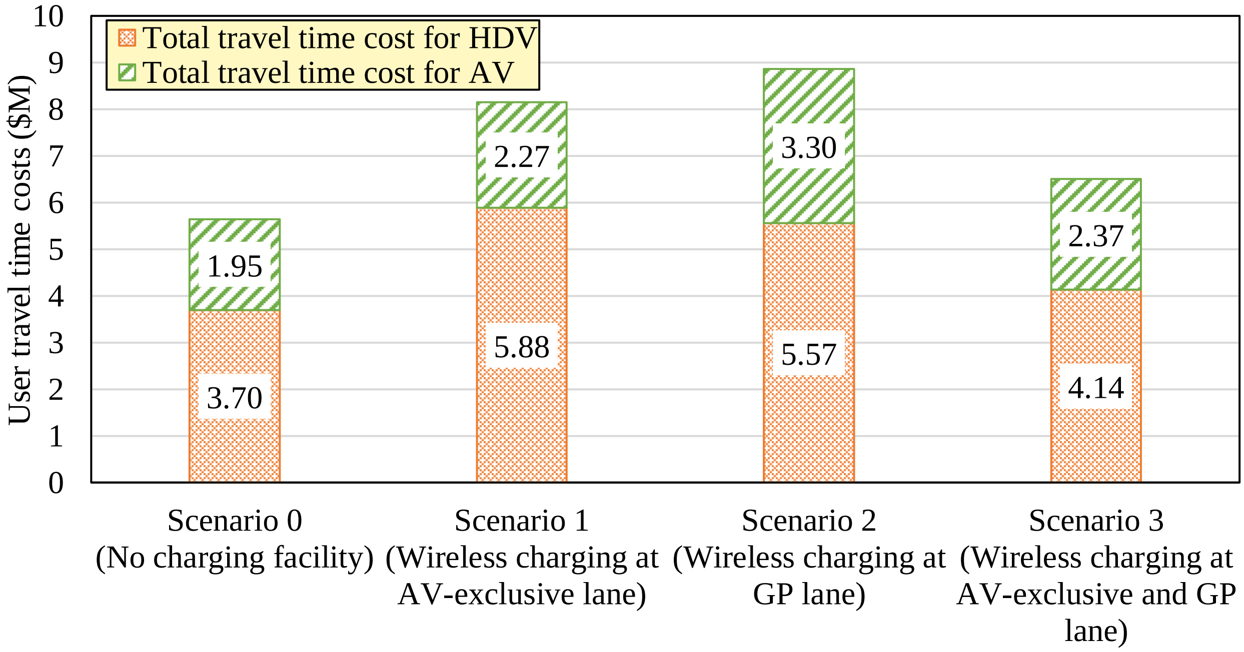
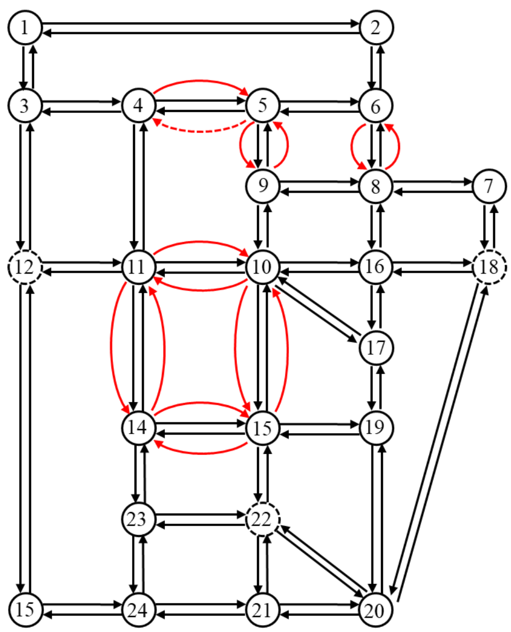
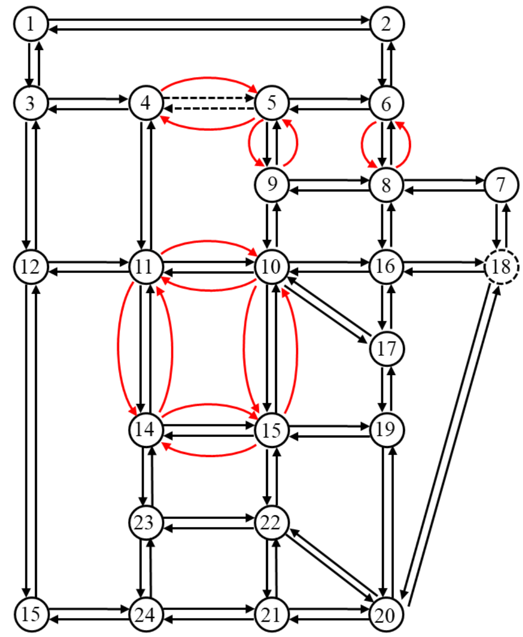


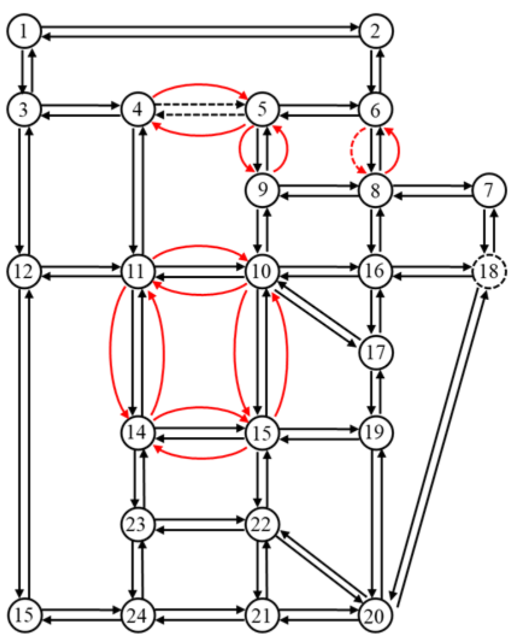
Figure 6.12. Comparison of results for general-purpose (GP) vs. AV-exclusive lanes selection for wireless-charging facility installation



(a) Scenario 1 (wireless charging at AV-exclusive lane)



(b) Scenario 2 (wireless charging at general-purpose lane)



(c) Scenario 3 (wireless charging at AV-exclusive and general-purpose lane)

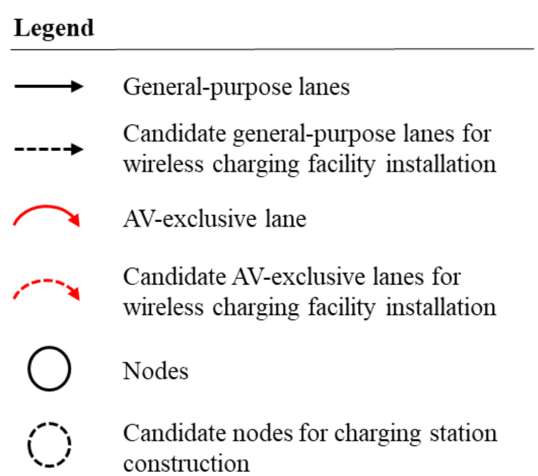


Figure 6.13 Optimal charging facility locations for scenarios involving general-purpose vs. AV-exclusive lanes for wireless-charging facility installation.

6.9 Sensitivity Analysis on the AV Purchase Price

In this section, we investigate the impacts of AV purchase price on AV market penetration. Consider three scenarios with different AV purchase prices: scenario 1 with high AV purchase price ($40,000), scenario 1 with medium AV purchase price ($30,000), and scenario 1 with low AV purchase price ($20,000). Table 6.8 presents the AV purchase price scenarios.

Table 6.8. AV purchase price scenarios.

AV purchase price scenario	AV purchase price
Scenario 1	$40,000
Scenario 2	$30,000
Scenario 3	$20,000

Figure 6.14 illustrates the AV market penetration for different AV purchase prices. In Scenario 3, AV and HDV purchase prices are assumed to be equal. In this scenario, the AV market penetration rate is 100%. This is an intuitive assumption because AV users' travel time is lower than that of HDV users and with same purchase price, travelers prefer to purchase AVs rather than HDV. By increasing the AV purchase price, the AV market penetration decreases, as shown in Figure 6.14.

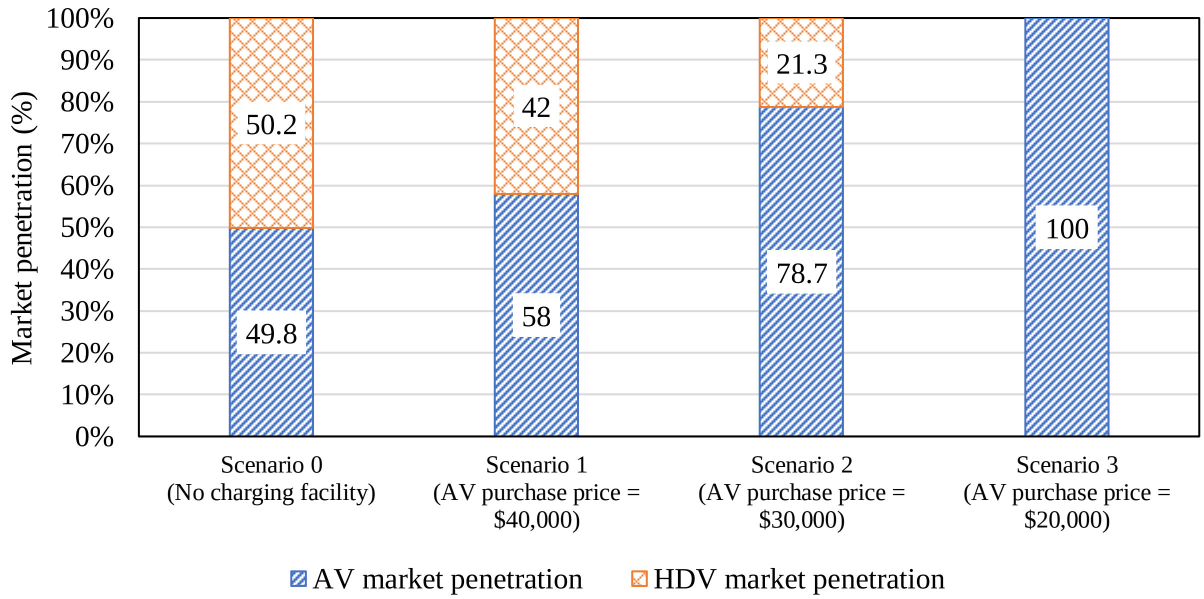


Figure 6.14 AV and HDV market penetration for the different AV purchase prices

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Figure 6.15 compares the AV and HDV users' travel time cost for different AV purchase price scenarios. The obtained results indicate that by decreasing the AV purchase price, the total travel time cost decreases. This is because by decreasing AV purchase price, as discussed above, the AV market penetration increases and consequently, the total travel time cost decreases. In Scenario 3, the total travel time cost is close to that of Scenario 0. This is due to the high AV market penetration, which improves network mobility and, as a result, decreases total travel time cost. As the AV purchase price decreases, the AV market share increases, resulting in total system travel time cost that is attributed mostly to AVs rather than HDVs; this explains why AV users' travel time increases as AV purchase price decreases.

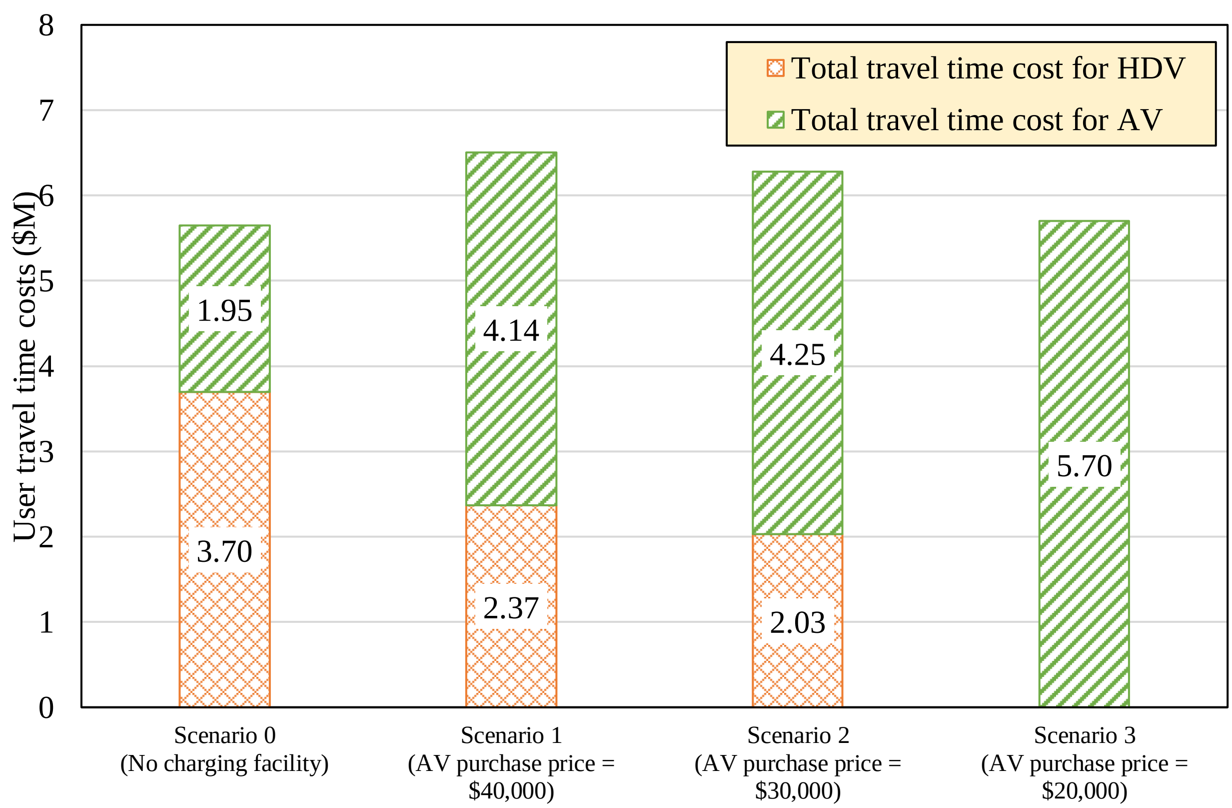


Figure 6.15 AV and HDV user travel time costs for different AV purchase prices

6.10 Sensitivity Analysis on the Driving Range

Finally, the impacts of the driving range of the electric AVs and electric HDVs, on construction costs, total travel time costs, and the AV market penetration rate trend, were investigated. It is important to carry out this analysis because the driving range is expected to increase over the years due to technological advancement (Zakaria et al., 2019). It is assumed that the driving range increases from 10 miles to 20 miles over the analysis period. Figure 6.16 presents the numerical results for different driving ranges. The results suggest that construction cost and total travel time cost decrease with higher driving range. This is because the driving range increases lead to reduced patronage of charging facilities. This reduces the need for investments charging facilities construction. On the other hand, the reduced patronage of charging facilities contributes to lower charging delay at charging facilities. Also, as the need for recharging is reduced due to increased driving range, travelers can meet their travel needs without deviating from their optimal routes, which reduces the total travel time cost.

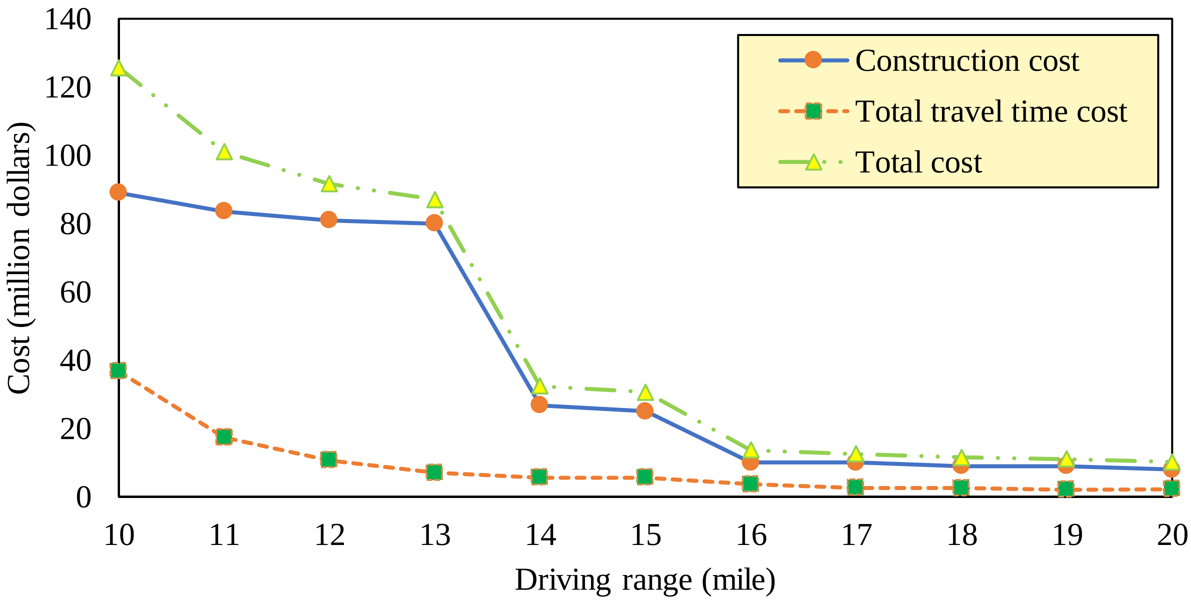


Figure 6.16 Impact of EV initial driving range on construction costs and total travel time costs

The impact of driving range on the AV market penetration was investigated. Figure 6.17 illustrates the impact of the EV driving range on the AV market penetration rates. It is clear that travelers recharging needs increase in the case of low driving ranges. Travelers experience more delay at charging facilities because they often need to deviate from their optimal routes to recharge, which leads to higher travel times. This ensures an increase in the AV market penetration. Due to the benefits earned by the introduction of AV the network (reflected in higher AV market penetration), the overall network travel time cost can be reduced. As the driving range increases, travelers recharging needs decrease, and consequently, charging delay is minimized. As a result, the difference of travel time for AV and HDV decreases. Since the purchase price of AV is higher than that of HDV, travelers prefer to purchase HDV rather than AV, and consequently, the AV market penetration decreases to the lowest level that EVs do not need to recharge (referred to as Scenario 0 discussed in Section 6.6).

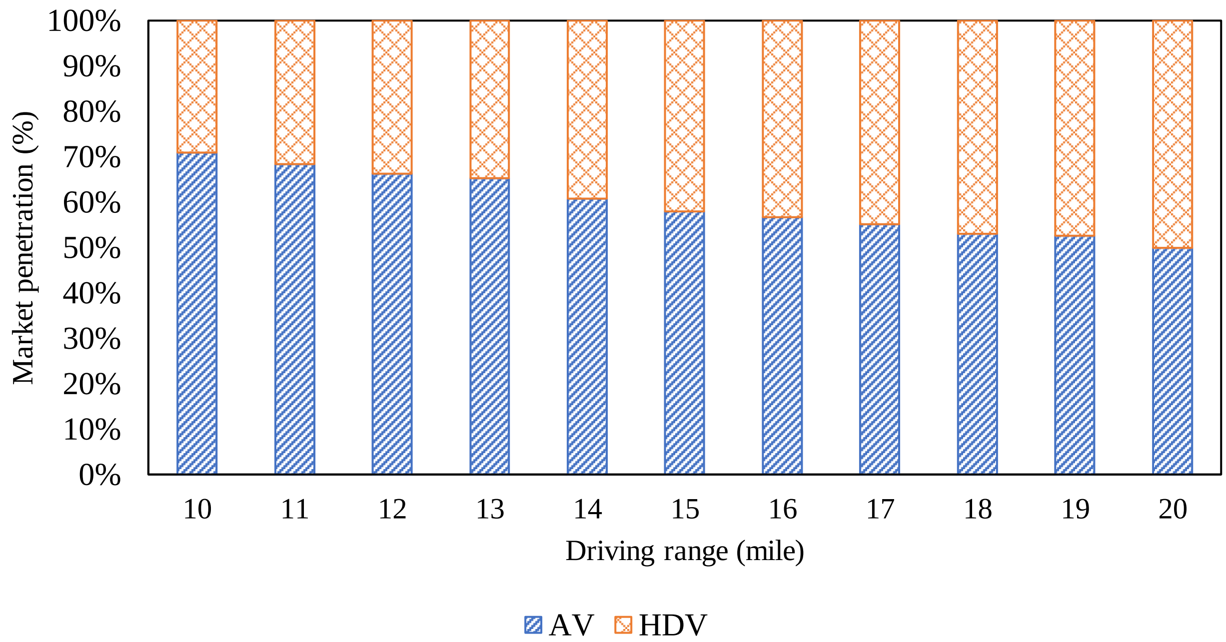


Figure 6.17 Impact of EV initial driving range on AVs market penetration.

6.11 Summary of the Chapter

This chapter presented the numerical results to test the capabilities of the proposed bi-level framework. First, a case study was defined in Section 6.1, and the base analyses obtained were discussed in Section 6.2. Sensitivity analysis was then carried out to understand the impact of following factors on the planning of charging facilities: agency-user cost weight ratio, EV charging investment budget, multiplicity of the EV charging types, lane type, EV driving range, and AV purchase price. A tradeoff between investment and EV charging facility construction was obtained. The results suggest that with increasing charging facility investment, a greater number of wireless-charging facilities (rather than charging stations) are prescribed for implementation. Furthermore, the sensitivity analyses indicated that providing multiple types of EV charging facilities and enabling both AV-exclusive and general-purpose lanes for wireless-charging facility installation, reduces the total system cost significantly. Finally, the chapter discusses the impacts of higher EV driving range and AV purchase price, on AV market share.

CHAPTER 7 CONCLUSIONS, LIMITATIONS, AND FUTURE WORK, FOR PART I OF THE STUDY

This chapter summarizes Part 1 of the study and highlights its findings and concluding remarks. Based on limitations of this study, the chapter then presents a variety of possible directions for future research.

7.1 Summary

The main objective of this part (Part 1) of the overall study is to provide and demonstrate a framework to determine the locations and capacities of charging facilities (stations and guideways) to serve a mixed fleet of human-driven vehicles (HDVs) and autonomous vehicles (AVs). This problem is formulated as a bi-level program with multi-objective optimization considerations. At the upper level, the transportation decision-makers, seek to minimize the total travel time cost and construction cost, and their decision-making variables are the locations of EV charging facilities and their operating capacity, subject to budgetary limitations. At the lower level, travelers' vehicle type (AV vs. HDV) choice is modeled using a utility-based logit function (a weighted sum of travel times and vehicle purchase prices). Travelers seek to minimize their travel time.

7.2 Findings and Conclusions

The proposed framework was tested using the Sioux-Falls road network. The numerical experiments suggest that if the transportation decision-makers set a higher value for a dollar of user's travel time compared to a dollar of agency's construction costs, the optimal plan will prescribe more wireless-charging facilities compared to the case where the agency dollar has a higher weight. As such, the increase in the construction budget generally motivates the optimal solution to include wireless-charging rather than charging stations. It is also found, intuitively, that the market penetration of AVs increases with higher budget levels. It is observed that providing more wireless-charging facilities reduces total travel time cost and, therefore, total weighted cost, which is also intuitive.

Further, the results suggest that, compared to the scenario where the transportation decision-makers construct charging stations only or where they construct wireless-charging facilities only, the scenario where they have the flexibility to construct either or both of them yields superior solutions (the total travel time cost decreases by 82% and 3%, respectively). It is also shown that emerging technologies such as AV, which is expected to reduce the value of travel time and improve road capacity (Correia et al., 2019; Tientrakool et al., 2011), can lead to significant cost savings in electric charging investments. It is shown that enabling wireless-charging facilities at both AV-exclusive and general-purpose lanes can reduce total travel time cost by 25% and 36% compared to plan where wireless-charging facilities are provided only at AV-exclusive and where they are provided at general-purpose lanes only, respectively.

Finally, the analyses of the driving range confirmed the extent to which travelers need to recharge more where driving range is low. As a result, travelers experience more charging delay and need to deviate more often from their optimal routes thus incurring higher travel times. This increases AV market penetration because AVs typically have lower travel times compared to HDVs and thus the" pain" incurred in longer travel times will be lower for AVs compared to HDVs. As a result, travelers will prefer purchasing AV rather than HDV. On the other hand, with an increasing driving range, the recharging need decreases, and as a result, recharging delay, and total travel time cost decrease. These cause a decrease in AV market penetration because the AV purchase price is higher compared to HDV and therefore may be less attractive to travelers for purchase.

7.3 Limitations of the Study

A limitation of this study is that the prospective locations for AV-exclusive lanes were considered to have been established as a part of the problem setting and therefore are not variable. As such, the proposed model does not establish optimal locations of the AV-exclusive lanes in the context of electric charging. Moreover, this study did not consider that commuting AVs could be recharged at parking facilities after dropping their passengers. This could impact the planning of EV charging facility locations. Another limitation of this study is that it did not consider different performance attributes of AVs and HDVs in the vehicle type purchase model, such as the higher safety benefits of AVs.

Furthermore, this study did not consider shared AVs. Although some researchers believe that most AVs in future, will be privately owned (Correia & van Arem, 2016; Saeed et al., 2020), It is reasonable to expect that shared AVs will represent a significant fraction of AVs (Overtoom et al., 2020), and their charging needs may differ from those of private AVs. Another limitation of this study is that it did not consider the scheduling of the EV charging facilities over time. Future work could consider a transition horizon consisting of multiple periods with a particular duration to capture the scheduling in planning for the EV charging facility problem.

Finally, although the proposed framework attempted to incorporate social equity concerns by considering charging facility patronage by both AV and HDV users, it is generally agreed that the advent of AVs will impact social equity in several ways besides equitable distribution of charging stations. For example, AVs can negatively impact social equity, due to their higher prices, as they will be relatively more accessible to higher-income earners, at least at earlier stages of their availability (Correia et al., 2019). On the other hand, in the context of AV-exclusive lane deployment, social equity concerns arise from the differences between AV and HDV purchase prices. In the early phases of AV operations, AV-exclusive lane deployment benefits will most likely be earned by higher-income or wealthier segments of the population.

7.4 Suggestions for Future Work

The findings of this study provide some directions for future research. First, considering the multi-period planning horizon is a natural extension of this study. As a result, agencies will be better equipped to assess and monitor the transition from current EV market penetration to full EV adoption. Considering a multi-period planning horizon not only addresses this study's limitation of EV's constituting 100% of the market, but also allows agencies to be better equipped to assess the scheduling of constructing EV charging facilities over the planning horizon within the long-term plans and also within their rather limited budgets. Second, in investigating the effects of AV-exclusive links, the locations of AV-exclusive links were assumed to be fixed in this study. Future research could develop a model that considers the location of AV-exclusive lanes to be variable. Third, more research on shared-AVs (SAVs) is needed to understand the comprehensive impact of SAVs on road networks. Fourth, in this study, the Sioux-Falls road network, which is a small network, was used to test the proposed framework. Larger networks may be considered in future studies. Finally, battery swapping (Gao et al., 2020) can be considered as a third option for EV charging modes, and could possibly contribute significantly to solving the wider problem of EV charging facility planning.

Part II

CHAPTER 8 INTRODUCTION TO PART II

8.1 Background and Motivation

The second part of the report develops an environmentally sustainable EV deployment plan for autonomous vehicles, such that travelers experience a smooth shift from ICEVs to EVs over a long planning timeline. The objective is to gradually convert the existing gasoline stations to electric charging stations, and to deploy new charging stations at new locations, to help meet transportation energy demand. Doing this is expected to help promote electric AVs and hopefully, achieve the goal of zero emissions in the next few decades. In the HDV-AV transition phase, it is anticipated that there will be locations that will serve ICEVs or EVs or both. A smooth transition is important because if any abrupt conversion of all gasoline stations to EV charging stations will mean that ICEV vehicles will be unable to satisfy their refueling needs. If charging stations are provided at a rate that is lower than EV adoption rate, then EV users will be left with insufficient access to charging stations, and this will discourage travelers from purchasing EVs. Therefore, any framework for designing an EV charging network must: (i) meet the charging needs of a growing number of EV (AV and HDV) consumers and (ii) address the expectedly diminishing albeit significant refueling needs of ICEV consumers over the long term. Also, such frameworks should be capable of translating the effect of the availability of EC changing charging infrastructure on EV market penetration over the planning timeline.

We define herein an optimization problem that has a bi-level structure. At the upper level, the transportation decision-maker seeks to minimize the total system vehicle emissions by adopting policies that develop optimal location of electric charging stations and gradually replacing the existing gasoline stations over the planning horizon. This involves identifying some locations for constructing new electric charging stations. The transportation decision-maker also makes decisions regarding the optimal capacities of the charging stations slated for deployment in each period. The planning decision is subject to budget constraints in each period, which is assumed to not carry over to future periods. At the lower level, travelers seek to minimize their travel times through their choice of routes and vehicle types based on the prescriptions made by the transportation decision maker at the upper level. The route choice of EVs is subject to driving range constraint while ICEV travelers are assumed to stop only once to refuel during their trips. In past research, the EV driving range has been incorporated in the analysis, in the context of intracity trips (Liu and Wang, 2017; Zheng et al., 2017). Such limitation in driving range may be due not only to current battery technology but also travelers' needs. For example, travelers may not have a charging port at their residences to charge their EVs daily. Even if they do, they may fail to remember to charge their vehicles at their residences and therefore will need to charge at a point during their trip. It is further assumed that the EV travelers have an additional cost that is due to the higher initial purchase cost of EVs compared to ICEVs, and that over the analysis timeline, such additional cost will decrease because of advances in technology. A diffusion model is applied to describe the vehicle type choice of travelers and to forecast the EV market penetration.

In this part of the report (see Pourgholamali (2023) for details), two types of vehicles are considered: EVs and ICEVs. Other vehicle types (hydrogen and plug-in hybrids) are not considered in order to reduce computational complexity. Ideally, the transition takes place over a long analysis timeline so that it is smooth rather than abrupt. Therefore, the transportation decision-maker adopts a multi-year analysis timeline, dividing this period into multiple sub-periods and determining the optimal number of EV charging stations, their locations and their respective operational capacities during each period. Furthermore, it is assumed that a certain fraction of ICEVs will need to refuel at a point along their trop; this fraction is held constant within a period but made to be variable from one period to the next. Finally, this report does not consider the emissions from power plants that produce the electricity for EVs.

There are four novel aspects of this part of the report. First, it considers ICEV refueling needs as part of the phased-transition plan toward fully adopting EVs over a planning horizon. Therefore, the study also incorporates the gradual conversion of existing gasoline refueling stations into electric charging stations. This accounts for the second contribution. This is an important equity issue. Next, this study adopts the objective of minimizing vehicle emissions as a basis for developing the optimal schedule for constructing EV charging stations. Third, in developing the EV charging station decisions, this study considers two key aspects related to the expected technological advancement of EVs over the planning horizon: EV driving range and EV extra ownership cost. To do this, the study assumes that the driving range of EVs varies over the planning horizon. It also considers the time-dependent additional cost of EVs relative to ICEVs because the EV purchase cost is expected to reduce over time due to technological advancement and scale economies of EV production.

8.2 Review of Past Work

The facility location problem at road networks has been widely investigated in several studies particularly to locate replenishing stations for fuels such as hydrogen (Kuby et al., 2009; Kuby and Lim, 2007; Lim and Kuby, 2010; Upchurch et al., 2009). In the context of locating electric charging stations, the literature can be classified into two groups. The first addresses locating electric charging station location where link travel times are assumed constant (Ghamami et al., 2016; Huang et al., 2015; Wu and Sioshansi, 2017). These studies are more appropriate for purely planning-phase evaluations or for intercity trips where travelers' route choices do not have a significant impact on the travel times. The second group (Chen et al., 2013, 2016a; Liu and Wang, 2017; Zheng et al., 2017) addresses electric charging station location at the infrastructure operations phase or at metropolitan areas, where it is prudent to consider congestion effects and travelers' route choices. The studies, which assume that the road link travel time depends on the flow at the link, are more appropriate in contexts where congestion plays an important role in travelers' route choices. This study falls into the latter group as it seeks to optimally locate electric charging stations while considering traffic congestion. Nevertheless, this study's framework is applicable to intercity networks and trips by not considering congestion effects and holding the link travel times at constant levels.

8.3 Research Gaps and Contributions

This study's facility-location based framework can facilitate the transition toward full adoption of electric automated vehicles. This enables the transport decision-maker to adopt policies that promote environmentally sustainable transportation systems with respect to vehicle emissions. Specifically, transport decision-makers need to gradually prepare the infrastructure so that travelers experience a smooth shift from ICEVs to EVs over a long planning horizon (e.g., 20 years in the case of France and the UK). In the context of vehicle fuel, the goal is to gradually migrate from gasoline propulsion (with energy served by gas stations) to electric propulsion (served by EV charging stations). Doing this will promote EVs and will help achieve the goal of zero emissions in the next few decades. It is anticipated that in this transition phase, there exist multi-energy stations (that, stations that serve both ICEVs and EVs). A smooth transition is important because if there is an abrupt change of all gas stations to charging stations (due to the transport agency decision-maker's policies), then ICEV consumers will not be able to fulfill their refueling demand requirements, giving rise to equity issues. Conversely, if the transport decision-maker (in conjunction with, or through the private sector) develops EV charging stations at a rate that falls short of the rate commensurate with EV adoption, then EV users will lack sufficient access to charging stations, and this will discourage travelers from purchasing EVs. Therefore, any framework for EV charging network design must: (i) meet the charging needs of a growing number of EV consumers and (ii) address the refueling needs of ICEV consumers over the long term. Also, any such framework should be capable of quantifying the impact of charging infrastructure availability on EV market penetration at any point in the planning horizon.

To address this research question, we define herein an optimization problem that has a bi-level structure. At the upper level, the transportation decision-maker seeks to minimize the total system vehicle emissions by adopting policies that develop optimal location of electric charging stations and replacing the existing gas stations over the planned horizon. This will involve identifying some new locations for new electric charging stations. The transportation decision-maker also makes decisions regarding the optimal capacities of the charging stations during each period. The planning decision is subject to budget constraints for each period, and the leftover budget is assumed to not carry over to future periods. At the lower level, travelers seek to minimize their travel time by making trip route and vehicle type choices based on the outcomes of the decisions made at the upper level. The EV travelers' route choices are subject to driving range constraint and each ICEV traveler is assumed to stop once during their trip to refuel. The driving range of EVs has been incorporated in the context of intracity trips in different studies (Liu and

Wang, 2017; Zheng et al., 2017). This limited driving range may be due not only to current battery technology but also to travelers' needs. For example, travelers may not have a charging port at their residences to charge their EVs daily. Even if they do, they may forget to charge their vehicles and therefore need to charge en route. It is assumed that EV travelers have an additional cost, which is measured as the extra cost of initial vehicle purchase cost (relative to an ICEV). It can be expected that this additional cost will decrease throughout the planning horizon due to technological advancements. A diffusion model is applied to capture the vehicle-type choice of travelers and to forecast the EV market penetration.

In this study, two types of vehicles are considered: EVs and ICEVs. Other vehicle types, (hydrogen fuel and plug-in hybrids, etc.) are not considered. It is assumed that the transition occurs over a planning horizon lengthy enough for the transition smoothening to be manifest. Therefore, the transportation decision-maker uses a multi-year planning horizon and divides this period into multiple periods and derives the optimal number of EV charging stations, and their locations and operational capacities during each period. Furthermore, it is assumed that a certain fraction of ICEVs needs to refuel en route, and this percentage is assumed to be constant within a period but varying across periods. Finally, this study does not consider the emissions associated with the power plants that produce the electricity for EVs.

In sum, the contributions of this study are fourfold. First, it considers ICEV refueling needs as part of the phased-transition plan toward fully adopting EVs over a planning horizon. Related to this research contribution is another contribution: the consideration of both brownfield development (gradual conversion of existing gas stations to electric charging stations) and greenfield development (deploying new charging stations to meet the energy demand), and the consideration of possible decommissioning of existing gas stations. This raises important equity issues, given the generally higher prices of EVs compared to HDVs. Third, this study considers vehicle emissions as the objective function of EV charging station construction framework. Fourth, in developing the EV charging station decisions, this study considers two key aspects related to the expected advancements in electric charging technology over the planning horizon: EV driving range and EV extra ownership cost. The study does this by considering growth in EV driving range over the planning horizon. Next, the study duly considers the time-dependent additional cost of EVs relative to ICEVs because the EV purchase cost is expected to reduce over time due to technological advancement and scale economies of EV production.

Finally, the study acknowledges that any framework for designing an EV charging network should: (i) meet the changing needs of a growing number of EV consumers, (ii) address the refueling needs of ICEV consumers over the long-term, (iii) be capable of translating the specific impact of charging infrastructure availability on EV market adoption over the planning horizon.

CHAPTER 9 METHODOLOGY

9.1 Preliminaries

Let $G = (N, A)$ represent the road network where N and A represent the set of nodes and links, respectively. There are two vehicle types, ICEVs and EVs. ICEVs are placed into two classes based on their refueling needs. Accordingly, the set of user classes is denoted by M which consists of: (i) Class 1, ICEVs without refueling need ($m = 1$), (ii) Class 2, ICEVs with refueling need ($m = 2$), and (iii) Class 3, EVs with recharging needs ($m = 3$). The set of nodes N consists of three types of nodes: (i) $\widehat{N}$ candidate nodes for electric charging stations, (ii) $\overline{N}$ nodes with existing refueling stations and (iii) other nodes $\overline{\overline{N}}$. It is assumed that nodes with existing refueling stations are also candidates for electric charging stations ($\overline{N} \subseteq \widehat{N}$) with fixed flow capacity f_i^t to serve both EVs and ICEVs. The travel time of link (i, j), σ_{ij}^t, follows a BPR (Bureau of Public Roads) function and is formulated as follows:

$$\sigma_{ij}^t = \theta_{ij}^t \left(1 + 0.15 \left(\frac{v_{ij}^t}{\chi_{ij}^t}\right)^4\right) \qquad \forall (i, j) \in A, \forall t \qquad 9.1$$

where θ_{ij}^t and χ_{ij}^t denote the free-flow travel time and capacity of link (i, j) in period t, respectively. The summary of notations is presented in Table 9.1.

9.2 The Bi-level Model

In this section, the EV charging station location problem is formulated as a bi-level program which consists of upper-level and lower-level models. Figure 9.1 presents the structure of bi-level problem. At the upper level, the transportation decision-maker (the agency and private-sector investor) seeks to minimize vehicle emissions and has the following decision variables: the locations of the prospective electric charging stations and their operating capacities, subject to budgetary limitations for each period of the planning horizon. It is assumed that the electric charging and refueling station capacities are sufficient to satisfy the travelers' needs. At the lower level, travelers aim to address their travel needs while keeping their travel costs at a minimum. Their decision variables: the route and the vehicle type (EV vs. ICEV). Thus, as the transportation decision-maker at the upper level provides EV charging stations, ICEV and EV travelers at the lower level respond by purchasing/using EVs and adjusting their route choices to reduce their travel times on trips that involve recharging/refueling. This also impacts the travel times of travelers with no recharging/refueling needs. It is also assumed that at user equilibrium condition, travelers are not able to reduce their travel time further by unilaterally changing their routes. Therefore, the route choice and vehicle type choice of the ICEV and EV travelers is influenced by their travel times and their need to recharge/refuel. In other words, it is important that the travelers' selected routes are not inconsistent with specified EV-driving ranges; also, the routes must contain nodes that have ICEV refueling stations.

Table 9.1 Summary of notations (For Part II of this report)

Sets	
N	Set of nodes
A	Set of links
M	Set of user classes
W	Set of O-D pairs
S	Set of origins
$\widehat{N}$	Set of nodes that are candidates for electric charging stations
$\overline{N}$	Set of nodes having existing gas refueling stations
$\overline{\overline{N}}$	Other nodes
Parameters	
θ_{ij}^t	Free-flow travel time of link (i,j) in period t
χ_{ij}^t	Capacity of link (i,j) in period t
f_i^t	Fixed-flow capacity of station i to serve both EVs and ICEVs in period t
c_i^k	Upgrade cost of station i from level $k-1$ to level k
p_i^k	Capacity of operating level k of station i
L_{ij}^t	Length of link (i,j) in period t
B^t	Budget for each period t
d^{t^*}	Potential EV market size of period t
η	Value of time
x^t	Extra cost of using EVs per trip compared to ICEVs in period t
$\hat{\varsigma}$	Diffusion model parameter
ϖ	Diffusion model parameter
Variables	
$y_i^{k,t}$	1 if the electric charging station of node i operates at level k in period t
φ_i^t	1 if the gas station of node i operates in period t and, 0 otherwise
$e_{ij}^{w,t,m}$	1 if link (i,j) is on the feasible path of user class m of origin-destination (O-D) pair w in period t.
$\alpha_i^{w,t}$	1 if ICEVs of O-D pair w stop at refueling station located at node i in period t
$\gamma_i^{w,t}$	Number of refueling stops of ICEVs of O-D pair w till node i in period t
σ_{ij}^t	Travel time of link (i,j) in period t
v_{ij}^t	Aggregate flow of link (i,j) in period t
$v_{ij}^{w,t,m}$	Flow of user class m on link (i,j) between O-D pair w in period t
$\zeta_i^{t,m}$	Refueling flow of user class m through station located at node i in period t
$d^{w,t,m}$	Travel demand of user class m between each O-D pair w in time period t
$h^{w,t}$	Intrinsic variable growth coefficient for O-D pair w in period t
$\pi_i^{w,t,m}$	Travel time of user class m between O-D pair w till node i in period t
$u_i^{w,t}$	Traveled distance of EVs of O-D pair w from the last charging station till node i in period t
$\phi_i^{w,t,m}$	Flow of user class m of O-D pair w on station located in node i in period t

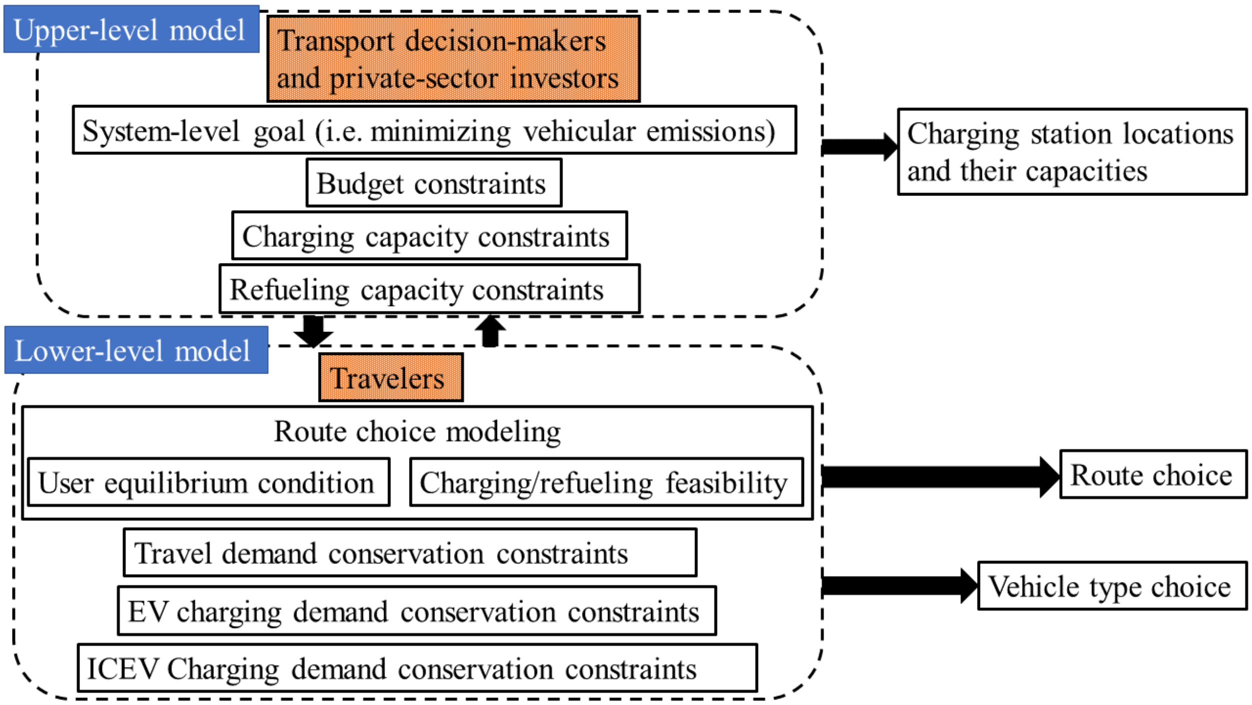


Figure 9.1 The bi-level nature of the problem context

9.3 The Upper-Level Model

As discussed earlier, the upper-level model addresses the decisions of the transportation decision-maker who seeks to minimize vehicle emissions by providing (through public agency policy and private-sector investment) electric charging stations at optimal locations and optimal capacities over a lengthy planning horizon. In this study, we use carbon monoxide (CO) as the indicator of vehicle emissions due to two reasons (Yin and Lawphongpanich, 2006): first, vehicles are the main source of CO emissions. Second, the patterns of emissions of other pollutants (such as, CO_2) are similar to that of CO. The CO emissions function $Y_{ij}^t(v_{ij}^t)$ (in g/veh) of link (i,j) in period t can be formulated as follows (Yin and Lawphongpanich, 2006):

$$Y_{ij}^t(v_{ij}^t) = 0.2038\sigma_{ij}^t(v_{ij}^t) \cdot \exp\left(\frac{0.7962L_{ij}^t}{\sigma_{ij}^t(v_{ij}^t)}\right) \qquad \forall (i,j) \in A, \forall t \qquad 9.2$$

where L_{ij}^t represent the length of link (i,j) (in kilometers) in period t, respectively. In equation (9.2), the travel time σ_{ij}^t of link (i,j) is in minutes. As traffic flow is assumed to consist of EVs and ICEVs, ICEVs are the only source of CO emissions. The vehicle emissions rate of the road network is equal to $\sum_t \sum_{(i,j)\in A} \sum_{m<3} v_{ij}^{w,t,m} Y_{ij}^t(v_{ij}^t)$ per unit of time (i.e., hr) through the planning horizon.

To adequately capture the construction cost of the electric charging station, such cost is defined as a function of the station operating capacity level which depends on the EV charging flow. Figure 9.2 illustrates the staircase nature of electric charging station construction based on the operating capacity. The construction cost of each electric charging station $i \in \widehat{N}$ is modeled as the staircase cost function c_i^k if the total flow of EVs of that station is between p_i^{k-1} and p_i^k. In other words, c_i^k is the upgrade cost for station i from level $k-1$ to level k. Let $\beta_i^{k,t}$ denote the total flow of EVs falling into operating level k interval $[p_i^{k-1}, p_i^k)$ of station i.

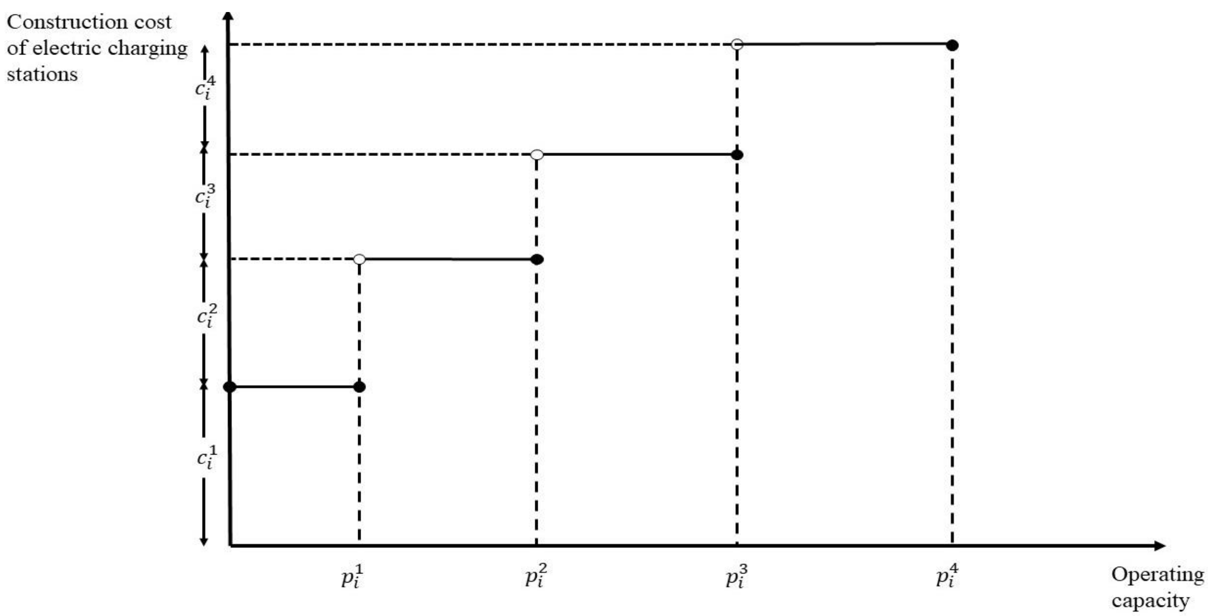


Figure 9.2 Staircase nature of the construction cost of electric charging stations

Let $y_i^{k,t}$ equal to 1 if the electric charging station of node i operates at level k in period t and, 0 otherwise. Further, through policy and private-sector investment, the transport decision-maker can cause a reduction in the number of gas stations and their eventual conversion to electric charging stations. Let φ_i^t be equal to 1 if the gas station of node i operates in period t and, 0 otherwise. Let $\zeta_i^{t,2}$ and $\zeta_i^{t,3}$ denote the refueling flow of ICEVs and charging flows of EVs through station located in node i in period t. The upper-level model is subject to budget constraints. The upper-level model can be formulated as follows:

$$\min_{\varphi,y,\zeta,\beta} Z^U = \sum_{t} \sum_{(i,j)\in A} \sum_{m<3} v_{ij}^{w,t,m} Y_{ij}^t\left(v_{ij}^t\right) \tag{9.3}$$

$$\sum_{(i,k)} c_i^k y_i^{k,1} \leq B^1 \tag{9.4}$$

8

$$\sum_{(i,k)} c_i^k \cdot \left(y_i^{k,t} - y_i^{k,t-1}\right) \leq B^t \qquad \forall t > 1 \qquad 9.5$$

$$\varphi_i^t \leq M \cdot \zeta_i^{t,2} \qquad \forall t, \forall i \in \bar{N} \qquad 9.6$$

$$\varphi_i^1 = 1 \qquad \forall i \in \bar{N} \qquad 9.7$$

$$\varphi_i^t \leq \varphi_i^{t-1} \qquad \forall t, \forall i \in \bar{N} \qquad 9.8$$

$$\beta_i^{k,t} \leq p_i^k y_i^{k,t} \qquad \forall t, \forall k, \forall i \in \hat{N} \qquad 9.9$$

$$\sum_k \beta_i^{k,t} = \zeta_i^{t,3} \qquad \forall t, \forall i \in \hat{N} \qquad 9.10$$

$$y_i^{k,t-1} \leq y_i^{k,t} \qquad \forall t, \forall k > 1, \forall i \in \hat{N} \qquad 9.11$$

$$y_i^{k,t}, \varphi_i^t \in \{0,1\} \qquad \forall (i,j) \in A, \forall i, \forall t, \forall k \qquad 9.12$$

$$\zeta_i^{t,m}, \beta_i^{k,t} \geq 0 \qquad \forall k, \forall i, \forall t, \forall m \qquad 9.13$$

The objective (Equation (9.3)) is to minimize the total vehicle emissions rate during the planning horizon. Constraint (9.4) states that the total construction cost of electric charging stations cannot exceed the budget in period 1. Constraints (9.5) ensure that the construction cost of electric charging stations does not exceed the available budget in period t. It states that if an electric charging station of node i does not exist in period $(t-1)$ of level k ($y_i^{k,t} = 0$), there is a need to invest c_i^k in period t to construct the charging station. On the other hand, if the electric charging station of node i exists in period $(t-1)$ ($y_i^{k,t} = 1$), then no cost is assigned. Also, constraints (9.6) state that if ICEVs do not use refueling station of node i in period t, it can be closed at that time. Constraints (9.7) state that existing refueling stations must serve ICEVs in the first period. Constraints (9.8) ensure that if refueling station of node i does not serve ICEVs in period $(t-1)$, it does not serve in period t (and for the rest of the planning horizon) as well. Constraints (9.9) and (9.10) address the operating level k of each electric charging station in time period t. Constraints (9.11) state that if the electric charging station at node i operates at level k in period t, it operates at least at the same level for the rest of the planning horizon. Constraints (9.12) and (9.13) indicate the domain of the decision variables.

9.4 The Lower-Level Model

The lower-level model is related to the vehicle type (or, vehicle "mode") and route choices of travelers under the policies and actions of the transportation decision-makers (including the private-sector investor) at the upper level. To capture the mode choice and adoption rate of EVs, this study applies a diffusion model. This model estimates the travel demand $d^{w,t,3}$ of EVs between each O-D pair w in period t. The model describes the EV adoption rate in each period as a function of the adoption rate and the EV's net benefit in the previous period. This model has been used widely in the literature to predict the adoption rate of new products including hydrogen fuel vehicles (Park et al., 2011) and automated vehicle technology (Chen et al., 2016a). Using the diffusion model, the EV adoption rate of period t is formulated herein as follows:

$$d^{w,t,3} = d^{w,t-1,3} + h^{w,t} \cdot \left(d^{w,t-1,3}\right) \cdot \left(1 - \frac{d^{w,t-1,3}}{d^{t^*}}\right) \qquad \forall t, \forall w \qquad 9.14$$

where d^{t^*} is the potential EV market size of period t. It can be realized in ideal situations with several refueling stations and comparable vehicle prices. Let $h^{w,t}$ denote the intrinsic variable growth coefficient for O-D pair w which is formulated as follows:

$$h^{w,t} = \hat{\varsigma} e^{\varpi \cdot \left(\eta\left(\pi_r^{w,t-1,2} - \pi_r^{w,t-1,3}\right) - x^{t-1}\right)} \qquad \forall t, \forall w \qquad 9.15$$

where $\hat{\varsigma}$ and ϖ are diffusion model parameters. Further, $\pi_r^{w,t-1,m}$ denotes the travel time of user class m between O-D pair w in period $(t-1)$ which implies that $\eta\left(\pi_r^{w,t-1,2} - \pi_r^{w,t-1,3}\right) - x^{t-1}$ is the net benefit (in terms of travel cost savings) gained by EV travelers compared to ICEV travelers who need to refuel.

To capture the driving range feasibility of EVs, the framework of the present study modified the single-period constraints proposed by Zheng et al. (2017) to yield a multiple-period setting. It is assumed that the electricity consumption of EVs is a linear function of travel distance. Further, EVs are assumed to be fully charged at their trip origin or after visiting the electric charging stations. Let R^t denote the range of EVs in period t which can increase over the planning horizon due to the advancement of EV technology. Let $u_i^{w,t}$ and $u'^{w,t}_i$ represent the traveled distance of EVs of O-D pair w from the last visited electric charging station in time period t. $u'^{w,t}_i$ is updated to zero at a charging station while $u_i^{w,t}$ should be less than or equal to driving range at every node. The multi-period EV driving range feasibility can be formulated as follows:

$$u_j^{w,t} \geq u'^{w,t}_i + L_{ij}^t - M \cdot \left(1 - e_{ij}^{w,t,3}\right) \qquad \forall (i,j) \in A, \forall w, \forall t \qquad 9.16$$
$$u_j^{w,t} \leq R^t \qquad \forall t, \forall w, \forall j \qquad 9.17$$
$$u'^{w,t}_i \geq u_i^{w,t} - M y_i^{1,t} \qquad \forall t, \forall w, \forall i \in \widehat{N} \qquad 9.18$$
$$u'^{w,t}_i \leq u_i^{w,t} + M y_i^{1,t} \qquad \forall t, \forall w, \forall i \in \widehat{N} \qquad 9.19$$
$$u'^{w,t}_s = 0 \qquad \forall s, \forall t, \forall w \qquad 9.20$$
$$u'^{w,t}_i \leq M \cdot \left(1 - y_i^{1,t}\right) \qquad \forall t, \forall w, \forall i \in \widehat{N} \qquad 9.21$$
$$-M\left(1 - e_{ij}^{w,t,3}\right) + \sum_{j:(j,i)\in A} v_{ji}^{w,t,3} \leq \phi_i^{w,t,3} \qquad \forall t, \forall w, \forall i \in \widehat{N} \qquad 9.22$$
$$M\left(1 - e_{ij}^{w,t,3}\right) + \sum_{j:(j,i)\in A} v_{ji}^{w,t,3} \geq \phi_i^{w,t,3} \qquad \forall t, \forall s, \forall i \in \widehat{N} \qquad 9.23$$
$$\phi_i^{w,t,3} \leq M \cdot y_i^{1,t} \qquad \forall i, \forall w, \forall t \qquad 9.24$$
$$\sum_w \phi_i^{w,t,3} = \zeta_i^{t,3} \qquad \forall t, \forall i \in \widehat{N} \qquad 9.25$$
$$u'^{w,t}_i, u_i^{w,t} \geq 0 \qquad \forall t, \forall w, \forall i \qquad 9.26$$
$$e_{ij}^{w,t,3} \in \{0,1\} \qquad \forall t, \forall w, \forall (i,j) \in A \qquad 9.27$$

where M is a large positive constant. $e_{ij}^{w,t,3}$ is a binary variable that indicates whether link (i,j) is on the feasible path based on the range constraint for EVs of O-D pair w in time period t.

Constraints (9.16) derive the distance that travelers originating from node s traveled from the last-visited charging station. Constraints (9.17) check whether the traveled distance is lesser than the driving range in period t. Constraints (9.18) - (9.19) ensure that if a charging station is located on node i, then $u'^{w,t}_i = u^{w,t}_i$ and then, constraints (9.21) update $u'^{w,t}_i$ to be equal to zero. This implies that traveled distance is set to zero after visiting the charging stations. Constraints 9.20 ensure that traveled distance is zero at the origin of the trips. Constraints)9.22) -)9.25) calculate the flow of EVs originated from node s to recharge in a station at node i in period t. Constraints (9.26) – (9.27) states the domain of the variables.

To model the refueling behavior of ICEVs of user class 2, this study analyzes the route choice of ICEV travelers who need to refuel per unit of time (i.e., hour) during intracity trips. This can be a typical hour where the refueling demand of travelers is at its peak. Some empirical studies suggest that refueling demand is highest during the evening peak period (San Diego Association of Governments, 2003). In this context, a certain percentage of ICEV travelers (class 2) are assumed to stop once to refuel per unit of time. In this report, this percentage is assumed to be given exogenously and known; however, ideally, it should be estimated using empirical data. Let $\alpha^{w,t}_i$ be equal to 1 if ICEVs of O-D pair w stop at refueling station located at node i in period t. Let $\gamma^{w,t}_i$ denote the number of refueling stops of ICEVs of O-D pair w till node i in period t. Let $\phi^{w,t,2}_i$ denote the refueling flow on station located in node i of O-D pair w in period t. Using these notations, the ICEV driving feasibility can be formulated as follows:

$$\gamma^{w,t}_j \geq \alpha^{w,t}_j + \gamma^{w,t}_i - M\left(1 - e^{w,t,2}_{ij}\right) \qquad \forall t, \forall w, \forall (i,j) \in A \qquad 9.28$$
$$\gamma^{w,t}_j \leq \alpha^{w,t}_j + \gamma^{w,t}_i + M\left(1 - e^{w,t,2}_{ij}\right) \qquad \forall t, \forall w, \forall (i,j) \in A \qquad 9.29$$
$$\gamma^{w,t}_s = 0 \qquad \forall t, \forall w, \forall s \in (N - \bar{N}) \qquad 9.30$$
$$\gamma^{w,t}_s \leq 1 \qquad \forall t, \forall w, \forall s \in \bar{N} \qquad 9.31$$
$$\gamma^{w,t}_r = 1 \qquad \forall t, \forall w, \forall r \qquad 9.32$$
$$-M\left(1 - \alpha^{w,t}_i\right) + \sum_{j:(j,i)\in A} v^{w,t,2}_{ji} \leq \phi^{w,t,2}_i \qquad \forall t, \forall w, \forall i \in \bar{N} \qquad 9.33$$
$$M\left(1 - \alpha^{w,t}_i\right) + \sum_{j:(j,i)\in A} v^{w,t,2}_{ji} \geq \phi^{w,t,2}_i \qquad \forall t, \forall s, \forall i \in \bar{N} \qquad 9.34$$
$$\phi^{w,t,2}_i \leq M \cdot \alpha^{w,t}_i \qquad \forall i, \forall w, \forall t \qquad 9.35$$
$$\sum_w \phi^{w,t,2}_i = \zeta^{t,2}_i \qquad \forall t, \forall i \in \bar{N} \qquad 9.36$$
$$\alpha^{w,t}_i \leq \varphi^t_i \qquad \forall t, \forall w, \forall i \in \bar{N} \qquad 9.37$$
$$\zeta^{t,2}_i + \zeta^{t,3}_i \leq f^t_i \qquad \forall t, \forall i \in \bar{N} \qquad 9.38$$
$$\alpha^{w,t}_i, \gamma^{w,t}_i, e^{w,t,2}_{ij} \in \{0,1\} \qquad \forall t, \forall w, \forall i, \forall (i,j) \in A \qquad 9.39$$
$$\phi^{w,t,2}_i, \zeta^{t,2}_i \geq 0 \qquad \forall t, \forall w, \forall i \in \bar{N} \qquad 9.40$$

where $e_{ij}^{w,t,2}$ indicates that link (i,j) belongs to the feasible subnetwork of ICEVs originating from node s in period t. In other words, $e_{ij}^{w,t,2}$ is equal to 1 if link (i,j) is on a feasible path for ICEVs of O-D pair w, and 0 otherwise. Constraints (9.28) and (9.29) calculate the number of refueling stops for each O-D pair w in period t. Constraints (9.30) ensure that the number of refueling stops of ICEVs is equal to zero before starting the trip at an origin without refueling station in period t. If there is a station located at the origin s of O-D pair w, constraint (9.31) states that ICEVs can refuel at origin in period t. Constraints (9.32) impose that ICEVs of O-D pair w, that need refueling, stop once before reaching their destination (node r) in period t. Constraints (9.33) – (9.35) calculate the refueling flow of ICEVs originated from node s in a station at node i in period t. Constraints (9.36) derive the refueling demand of a station located at node i in period t. Constraints (9.37) ensure that ICEVs do not stop at node i if a refueling station does not exist at that node in period t. Constraints (9.38) ensure that the total refueling (derived by equation (9.36)) and charging flows (derived by equation (9.25)) do not exceed the capacity of station i in period t. Constraints (9.39) and (9.40) determine the domains of the variables.

Next, we formulate the multi-class traffic assignment subject to the decisions of the transport decision-makers made at the upper level. It is important that the traffic assignment satisfies the EV range limitations and the ICEV refueling stops. As such, equilibrium conditions could be achieved using a feasible subnetwork defined by $e_{ij}^{w,t,m}$, and the lower-level traffic assignment can then be formulated as follows:

$$\min Z^L = \sum_{(i,j)\in A} \int_0^{v_{ij}^t} \sigma_{ij}^t(\omega) d\omega \qquad 9.41$$

$$\sum_{(w,m)} v_{ij}^{w,t,m} = v_{ij}^t \qquad \forall (i,j) \in A, \forall t \qquad 9.42$$

$$\sum_{j:(j,i)\in A} v_{ji}^{w,t,m} - \sum_{j:(i,j)\in A} v_{ij}^{w,t,m} = q_i^{w,t,m} \qquad \forall w, \forall i, \forall t, \forall m \qquad 9.43$$

$$v_{ij}^{w,t,m} \le M \cdot e_{ij}^{w,t,m} \qquad \forall (i,j) \in A, \forall w, \forall t, m > 1 \qquad 9.44$$

$$v_{ij}^{w,t,m} \ge 0 \qquad \forall (i,j) \in A, \forall w, \forall t, \forall m \qquad 9.45$$

where $q_i^{w,t,m}$ is defined as follows:

$$q_i^{w,t,m} = \begin{cases} -d^{w,t,m} & \text{if } i \text{ is the origin of O} - \text{D pair w} \\ 0 & \text{if } i \text{ is an intermediate nodes} \\ d^{w,t,m} & \text{if } i \text{ is the destination of O} - \text{D pair w} \end{cases} \qquad \forall w, \forall i, \forall t, \forall m \qquad 9.46$$

The model (equations)9.41) -)9.45)) is the traditional model for static traffic assignment with an additional constraint (Equation 9.44). This constraint restricts user classes 2 and 3 to their corresponding feasible subnetworks only.

CHAPTER 10 SOLUTION ALGORITHM

10.1 Introduction

The bi-level model (equations (9.3) – (9.40)) consists of lower-level and upper-level models both of which can be solved using commercial solvers. This mathematical program has equilibrium constraint (MPEC) that has mixed integer and complementarity constraints, rendering it rather difficult to solve. As such, in this study, we solve the MPEC (equations (9.3) – (9.40)) using the active-set algorithm (Zhang et al., 2009). This chapter of the report provides details of the solution algorithms.

10.2 Problem Reformulation and Solution Algorithm

To develop a tractable bi-level formulation that can be solved by commercial solvers, it is necessary to formulate the first-order condition of model 9.41 – 9.45 to eliminate the objective function)9.41). Let $\pi_i^{w,t,m}$denote a Lagrangian multiplier of travel demand conservation constraints (equation)9.43)) which is the minimum cost of user class m to travel to node i between O-D pair w in period t. Let $\rho_{ij}^{w,t,m}$ denote the Lagrangian multiplier of constraints)9.44). The first-order condition of model)9.41) – (9.45) can be written as follows:

$$v_{ij}^{w,t,1}\cdot\left(\sigma_{ij}^{t}\left(v_{ij}^{t}\right)+\pi_i^{w,t,1}-\pi_j^{w,t,1}\right)=0 \qquad \forall(i,j)\in A,\forall w,\forall t \tag{9.47}$$

$$\sigma_{ij}^{t}\left(v_{ij}^{t}\right)+\pi_i^{w,t,1}-\pi_j^{w,t,1}\geq 0 \qquad \forall(i,j)\in A,\forall w,\forall t \tag{9.48}$$

$$v_{ij}^{w,t,m}\cdot\left(\sigma_{ij}^{t}\left(v_{ij}^{t}\right)+\rho_{ij}^{w,t,m}+\pi_i^{w,t,m}-\pi_j^{w,t,m}\right)=0 \qquad \forall(i,j)\in A,\forall w,\forall t,m>1 \tag{9.49}$$

$$\sigma_{ij}^{t}\left(v_{ij}^{t}\right)+\rho_{ij}^{w,t,m}+\pi_i^{w,t,m}-\pi_j^{w,t,m}\geq 0 \qquad \forall(i,j)\in A,\forall w,\forall t,m>1 \tag{9.50}$$

$$v_{ij}^{w,t,m}\leq M\cdot e_{ij}^{w,t,m} \qquad \forall(i,j)\in A,\forall w,\forall t,m>1 \tag{9.51}$$

$$\rho_{ij}^{w,t,m}\leq M\cdot\left(1-e_{ij}^{w,t,m}\right) \qquad \forall(i,j)\in A,\forall w,\forall t,m>1 \tag{9.52}$$

$$\pi_s^{w,t,m}=0 \qquad \forall w,\forall s,\forall t,\forall m \tag{9.53}$$

$$\sum_{j:(j,i)\in A}v_{ji}^{w,t,m}-\sum_{j:(i,j)\in A}v_{ij}^{w,t,m}=q_i^{w,t,m} \qquad \forall w,\forall i,\forall t,\forall m \tag{9.54}$$

$$\rho_{ij}^{w,t,m},v_{ij}^{w,t,m},\pi_i^{w,t,m}\geq 0 \qquad \forall(i,j),\forall w,\forall t,\forall m \tag{9.55}$$

Constraints)9.47) – (9.48) are the user equilibrium condition for user class 1 which ensure that if travelers 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)9.49) – (9.50) are the user equilibrium condition for user classes 2 and 3. They also indicate that if link (i,j) does not belong to feasible path, there is extra perceived cost for travelers which prevents to utilize this link by travelers. Constraint (9.51) makes sure that there is no traffic flow on infeasible paths. Constraints)9.52) state that if a link (i,j) does not belong to the feasible subnetwork of user class 2 and 3, then there is an extra perceived cost for using link (i,j). Constraint (9.54) is identical to constraints)9.43). Constraint)9.55) defines the domains of the variables. Finally, the bi-level model ()9.3) –)9.40),)9.47) – (9.55)) includes both upper-level and lower-level models which can be solved using commercial solvers. In the present study, Zhang et al. (2009)'s active-set algorithms are used to solve the MPEC ()9.3) – (9.40),)9.47) –)9.55)) because such mathematical programs with equilibrium constraint (MPEC) (that have mixed-integer and complementarity constraints) are rather difficult to solve.

The proposed bi-level model ()9.3) –)9.40),)9.47) –)9.55)) can be classified as a discrete network design problem (DNDP). It consists of two sets of complementarity constraints ()9.3) –)9.40),)9.47) –)9.55)) and five sets of binary variables $(\alpha_i^{w,t}, \gamma_i^{w,t}, e_{ij}^{w,t,m}, y_i^{k,t}, \varphi_i^t)$. In the literature, a number of solution algorithms have been proposed to solve the DNDP, such as support-function based methods, branch-and-bound technique, and active-set algorithms. This study uses the active-set algorithm with the basic idea of solving a sequence of index-set-based constrained bi-level model. This algorithm is initialized by providing a feasible design of charging stations location and then, dual variables of index-set-based constraints are used to update the feasible design. Let us define the active sets for binary variables with dividing them into two sets based on their values in each iteration, as follows:

- $\Omega(y) = \{(i,k,t) \mid y_i^{k,t} = 0\}$, $\Omega^c(y) = \{(i,k,t) \mid y_i^{k,t} = 1\}$,
- $\Omega(\varphi) = \{(i,t) \mid \varphi_i^t = 0\}$, $\Omega^c(\varphi) = \{(i,t) \mid \varphi_i^t = 1\}$,
- $\Omega(\alpha) = \{(i,w,t) \mid \alpha_i^{w,t} = 0\}$, $\Omega^c(\alpha) = \{(i,w,t) \mid \alpha_i^{w,t} = 1\}$,
- $\Omega(\gamma) = \{(i,w,t) \mid \gamma_i^{w,t} = 0\}$, $\Omega^c(\gamma) = \{(i,w,t) \mid \gamma_i^{w,t} = 1\}$,
- $\Omega(e) = \{((i,j),w,t,m) \mid e_{ij}^{w,t,m} = 0\}$, $\Omega^c(e) = \{((i,j),w,t,m) \mid e_{ij}^{w,t,m} = 1\}$

Then, the index-set-based (ISB) model can be formulated as follows:

$$\min_{v} Z^U = \sum_{t} \sum_{(i,j)\in A} \sum_{m<3} v_{ij}^{w,t,m} Y_{ij}^t\left(v_{ij}^t\right) \tag*{9.56}$$

$$y_i^{k,t} = 0 \qquad \forall (i,k,t) \in \Omega(y) \tag*{9.57}$$

$$y_i^{k,t} = 1 \qquad \forall (i,k,t) \in \Omega^c(y) \tag*{9.58}$$

$$\varphi_i^t = 0 \qquad \forall (i,t) \in \Omega(\varphi) \tag*{9.59}$$

$$\varphi_i^t = 1 \qquad \forall (i,t) \in \Omega^c(\varphi) \tag*{9.60}$$

$$\alpha_i^{w,t} = 0 \qquad \forall (i,w,t) \in \Omega(\alpha) \tag*{9.61}$$

$$\alpha_i^{w,t} = 1 \qquad \forall (i,w,t) \in \Omega^c(\alpha) \tag*{9.62}$$

$$\gamma_i^{w,t} = 0 \qquad \forall (i,w,t) \in \Omega(\gamma) \tag*{9.63}$$

$$\gamma_i^{w,t} = 1 \qquad \forall (i,w,t) \in \Omega^c(\gamma) \tag*{9.64}$$

$$e_{ij}^{w,t,m} = 0 \qquad ((i,j),w,t,m) \in \Omega(e) \tag*{9.65}$$

$$e_{ij}^{w,t,m} = 1 \qquad ((i,j),w,t,m) \in \Omega^c(e) \tag*{9.66}$$

9.4–9.11, 9.14–9.27, 9.28-9.38, 9.40, 9.47-9.55

Although ISB still consists of complementarity constraints, it is much easier to solve compared to the MPEC ((9.3) –)9.40),)9.47) – (9.55)) by fixing the binary variables. Let $z_i^{1,k,t}$, $z_i^{2,t}$, $z_i^{3,w,t}$, $z_i^{4,w,t}$, $z_{ij}^{5,w,t,m}$ be binary variables that indicate whether to flip the value of $y_i^{k,t}$, φ_i^t, $\alpha_i^{w,t}$, $\gamma_i^{w,t}$, and $e_{ij}^{w,t,m}$, respectively. To update the current locations of charging and refueling stations, the Lagrangian multipliers of constraints)9.57) –)9.66), denoted by $\mu_i^{1,k,t}$, $\mu_i^{21,k,t}$, $b_i^{1,t}$, $b_i^{2,t}$, $\lambda_i^{1,w,t}$, $\lambda_i^{2,w,t}$, $\tau_i^{1,w,t}$, $\tau_i^{2,w,t}$, $\kappa_{ij}^{1,w,t,m}$ and $\kappa_{ij}^{2,w,t,m}$, are used to develop the following knapsack problem (KP):

$$\min_{z} \sum_{t}((b_i^{1,t} g_i^t - b_i^{2,t} g_i^t) + \sum_{(i,k)}\left(\mu_i^{1,k,t} z_i^{k,t} - \mu_i^{2,k,t} z_i^{k,t}\right) + \sum_{(i,w)}\left(\lambda_i^{1,w,t}\psi_i^{w,t} - \lambda_i^{2,w,t}\psi_i^{w,t}\right) + \sum_{(i,w)}\left(\tau_i^{1,w,t} o_i^{w,t} - \tau_i^{2,w,t} o_i^{w,t}\right) + \sum_{((i,j),w,m)}\left(\kappa_{ij}^{1,w,t,m}\epsilon_{ij}^{w,t,m} - \kappa_{ij}^{2,w,t}\epsilon_{ij}^{w,t,m}\right)) \quad 9.67$$

$$y_i^{k,t} = z_i^{k,t} \qquad \forall (i,k,t) \in \Omega(y) \quad 9.68$$

$$y_i^{k,t} = 1 - z_i^{k,t} \qquad \forall (i,k,t) \in \Omega^c(y) \quad 9.69$$

$$\varphi_i^t = g_i^t \qquad \forall (i,t) \in \Omega(\varphi) \quad 9.70$$

$$\varphi_i^t = 1 - g_i^t \qquad \forall (i,t) \in \Omega^c(\varphi) \quad 9.71$$

$$\alpha_i^{w,t} = \psi_i^{w,t} \qquad \forall (i,w,t) \in \Omega(\alpha) \quad 9.72$$

$$\alpha_i^{w,t} = 1 - \psi_i^{w,t} \qquad \forall (i,w,t) \in \Omega^c(\alpha) \quad 9.73$$

$$\gamma_i^{w,t} = o_i^{w,t} \qquad \forall (i,w,t) \in \Omega(\gamma) \quad 9.74$$

$$\gamma_i^{w,t} = 1 - o_i^{w,t} \qquad \forall (i,w,t) \in \Omega^c(\gamma) \quad 9.75$$

$$e_{ij}^{w,t,m} = \xi_{ij}^{w,t,m} \qquad ((i,j),w,t,m) \in \Omega(e) \quad 9.76$$

$$e_{ij}^{w,t,m} = 1 - \xi_{ij}^{w,t,m} \qquad ((i,j),w,t,m) \in \Omega^c(e) \quad 9.77$$

$$\sum_t((b_i^{1,t} g_i^t - b_i^{2,t} g_i^t) + \sum_{(i,k)}\left(\mu_i^{1,k,t} z_i^{k,t} - \mu_i^{2,k,t} z_i^{k,t}\right) + \sum_{(i,w)}\left(\lambda_i^{1,w,t}\psi_i^{w,t} - \lambda_i^{2,w,t}\psi_i^{w,t}\right) + \sum_{(i,w)}\left(\tau_i^{1,w,t} o_i^{w,t} - \tau_i^{2,w,t} o_i^{w,t}\right) + \sum_{((i,j),w,m)}\left(\kappa_{ij}^{1,w,t,m}\epsilon_{ij}^{w,t,m} - \kappa_{ij}^{2,w,t}\epsilon_{ij}^{w,t,m}\right)) \geq \varrho \quad 9.78$$

9.4 – 9.13

$$g, z, \psi, o, \xi \in \{0,1\} \quad 9.79$$

Constraints)9.68) and (9.69) state that if $z_i^{k,t} = 1$, then the value of $y_i^{k,t}$ needs to be flipped. Similarly, constraints)9.70) and)9.71) indicate that if $g_i^t = 1$, then the value of φ_i^t needs to be flipped. Also, constraints (9.72) – (9.73), (9.74) – (9.75), and (9.76) – (9.77) flip the values of $\alpha_i^{w,t}$, $\gamma_i^{w,t}$ and $e_{ij}^{w,t,m}$ using binary variables $\psi_i^{w,t}$, $o_i^{w,t}$, and $\xi_{ij}^{w,t,m}$, respectively. Constraint (9.78) is introduced to ensure the decrease in total system emissions. This is because the Lagrangian multipliers indicate the change in objective function with marginal changes of binary variables. However, the actual changes of binary variables are equal to 1. Hence, if the KP problem does not lead to a reduction of the objective function, the value of ϱ increases by small positive constant δ in constraint (9.78) to force the problem to generate another feasible design. Constraints (9.4) – (9.40) ensure the design feasibility. The solution algorithm to solve the bi-level model ((9.3) – (9.40), (9.47) – (9.55)) is presented in Figure 10.1.

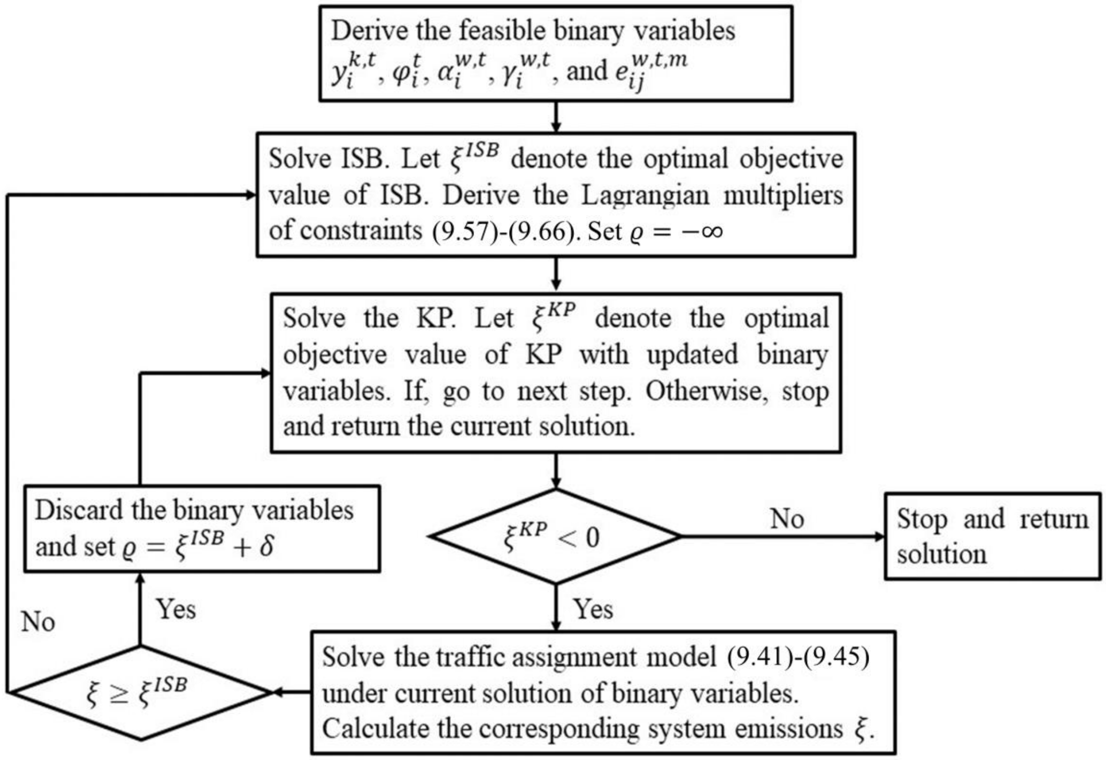


Figure 10.1 Solution algorithm

CHAPTER 11 NUMERICAL EXPERIMENTS

11.1 Problem Setting

In this study, we carried out computational experiments to demonstrate the applicability of the proposed model. The electric charging location problem is solved for the Sioux-Falls network with 24 nodes and 76 links. The characteristics of the Sioux-Falls network can be found in Leblanc et al. (1975). Following the settings proposed by Zheng et al. (2017), there are 72 O-D pairs where the number of origins is limited to 3 (nodes 1,2 and 3). Travel demand grows at the rate of 5% throughout the planning horizon. The planning horizon is divided into five periods. The candidate nodes for locating a charging station are shown in red and yellow in Figure 11.1. The existing refueling stations are located on nodes 4, 10, 12, 14, 18, 20 and 22. The driving range of each EV is assumed to be 12 miles, a value which is used in other studies (Jing et al., 2017; Xie and Jiang, 2016; Zheng et al., 2017) for illustration purposes. The report uses this network simply for illustration purposes.

In this example, for each charging station, we consider two operating levels. The first level capacity p_i^1, is 300 veh/hr with construction cost c_i^1 of $100,000. The second-level capacity p_i^2 is 400 veh/hr with construction cost c_i^2 of $200,000. For nodes 16 and 17, the construction costs for operating levels 1 and 2 are equal to $200,000 and $400,000, respectively. This is because, it is necessary to build new stations at these nodes as no gas station exists at these nodes. The fixed-flow capacity f_i^t of a refueling station to serve both ICEVs and EVs is 600 ve/hr. Without constructing the EV charging stations, the total vehicle emissions rate under user equilibrium conditions is 432.52 kg/hr through the planning horizon.

The present study assumes that the initial market share of EVs is 5% and that the potential market size is 75% of the prevailing traffic stream. The two parameters in equation (9.15), ϖ and $\hat{\varsigma}$, are assumed to be 0.03 and 0.5, respectively (Chen et al., 2016b). Further, it is assumed that: the value of time for the drivers is 20 ($/hr); and 15% of ICEVs need to refuel each hour. The results are obtained using GAMS (Rosenthal, 2015) on one cluster node with four 2.3-GHz 12-core AMD Opteron 6176 processors and 192 GB RAM per node. It may be noted that the parameter values that are used in this section are primarily for illustrative purposes and for testing the model.

First, we seek to investigate the impact of construction budget on the market penetration of EVs through the planning horizon. As explained above, in this analysis, the vehicle range is assumed to be 12 miles. The construction budget levels have two scenarios: in the first and second scenarios, the EV station construction budget for periods 1-5 is assumed to be $100,000 and $200,000, respectively, in each period.

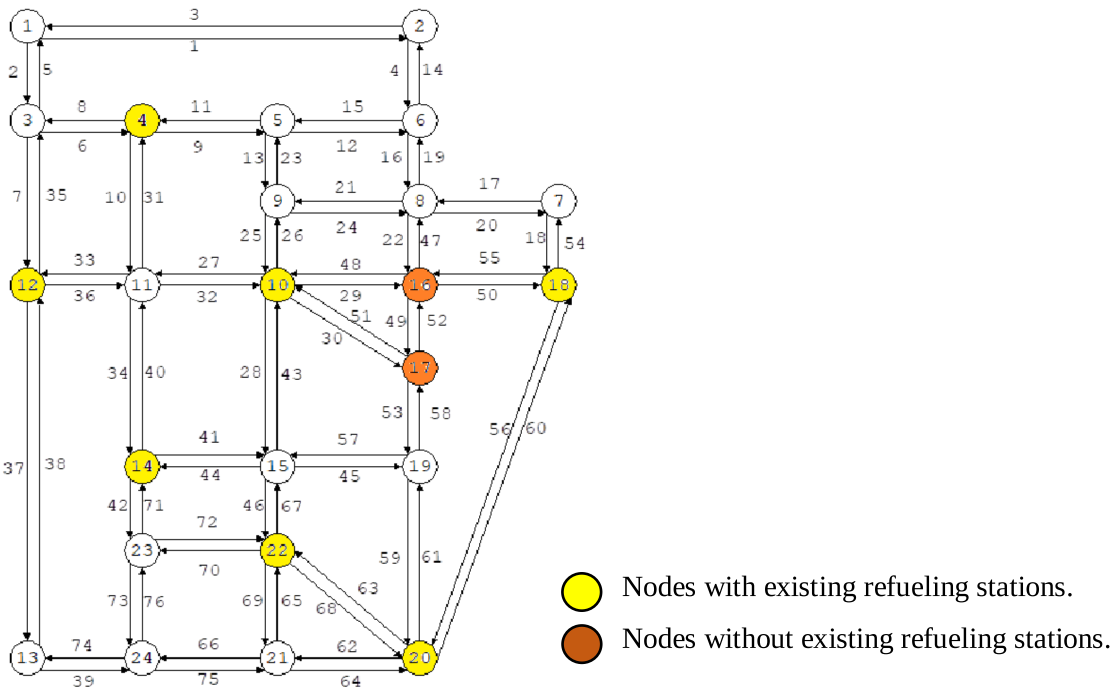
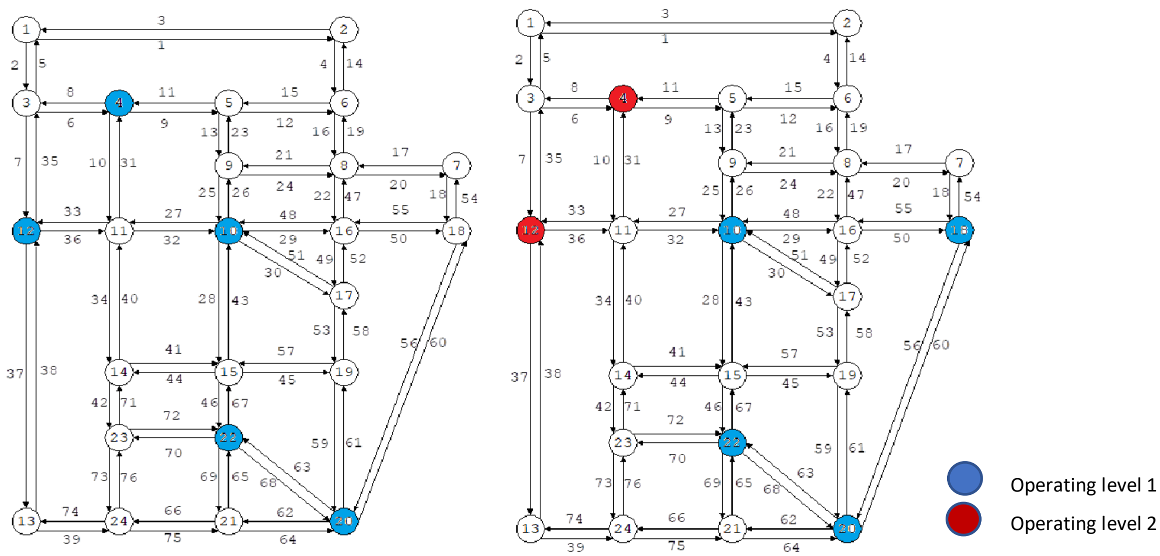


Figure 11.1 Sioux-Falls network with candidate charging station locations.

11.2 Results and Discussion

Figure 11.2 presents the nodes selected for electric charging station construction under different budget scenarios and Figure 11.3 illustrates the impact of the EV station construction budget on EV market penetration rates. Under budget scenario 1, the electric charging stations on nodes 4, 10, 12, 20, and 22 are constructed in periods 1, 2, 3, 4, and 5 in operating level 1, respectively. The resulting vehicle emissions rate under budget scenario 1 is 232.37 kg/hr through the planning horizon; this is a drastic reduction compared to the case without electric charging stations. As can be seen under the model assumptions, the construction of the electric charging stations can significantly increase the EV market penetration.

Under the second budget scenario, the electric charging stations are constructed to operate at level 1 at nodes 4 and 12 in period 1, at nodes 18 and 20 in period 2, and at nodes 10 and 22 in period 4. The electric charging stations at nodes 4 and 12 are upgraded to operate at level 2 in periods 3 and 5, respectively. It should be noted that nodes 16 and 17 are not selected under the optimal plan for constructing electric charging stations due to higher construction cost compared to nodes with existing gas refueling stations. The resulting vehicle emissions for budget scenario 2 are 209.636 kg/hr through the planning horizon. This demonstrates that a higher construction budget, over a given period, can result in a reduction of the local vehicle emissions and higher EV market share as it leads to higher accessibility for EV travelers to electric charging stations. Hence, the transport decision-makers need to consider the trade-off between the higher investment in construction costs of the charging networks and the monetary costs associated with the impact of higher vehicle emissions on human lives and environment. Therefore, to address the objectives of the Paris Agreement that aims to reduce GHG emissions to be lesser than certain level, it is critical to conduct sensitivity analysis to identify the planning horizon budget needed to achieve those emission standards.



(a) Nodes selected under budget scenario 1 (b) Nodes selected under budget scenario 2

Figure 11.2 Selected nodes for electric charging station construction under different budget scenarios

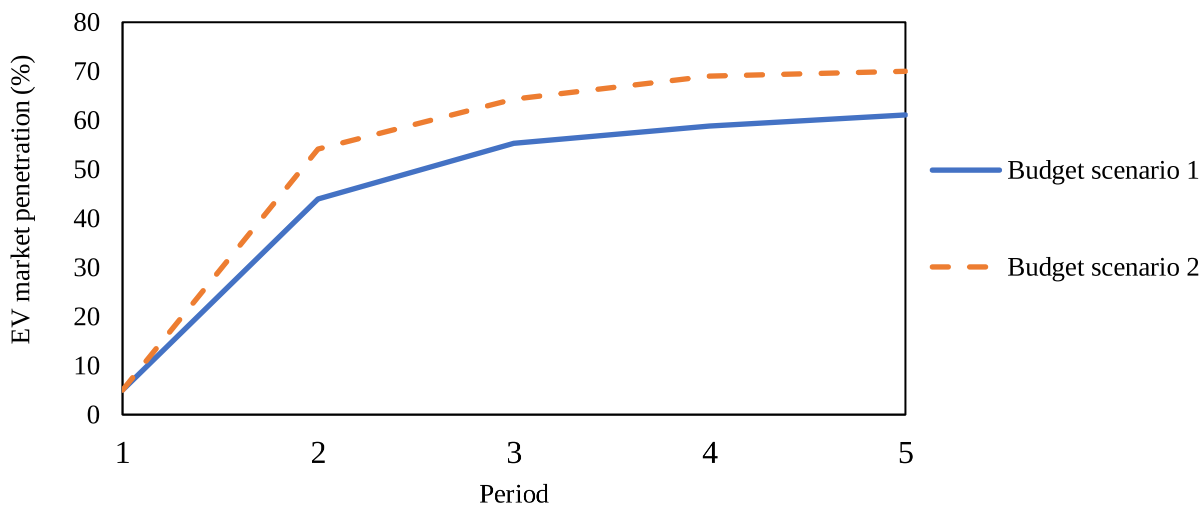
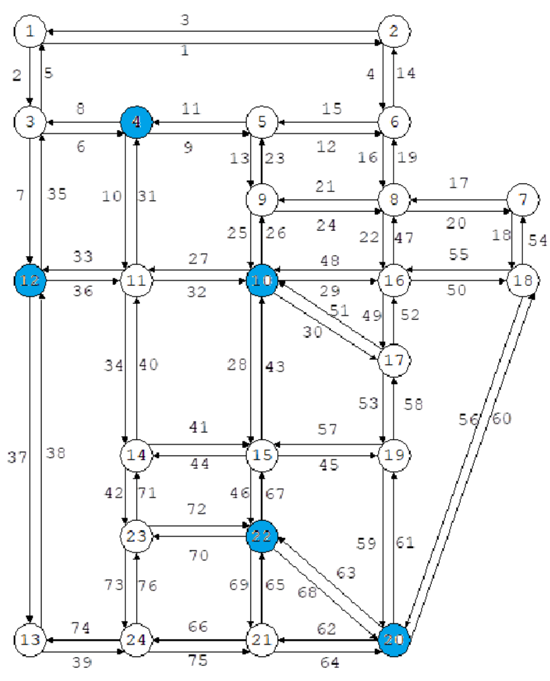


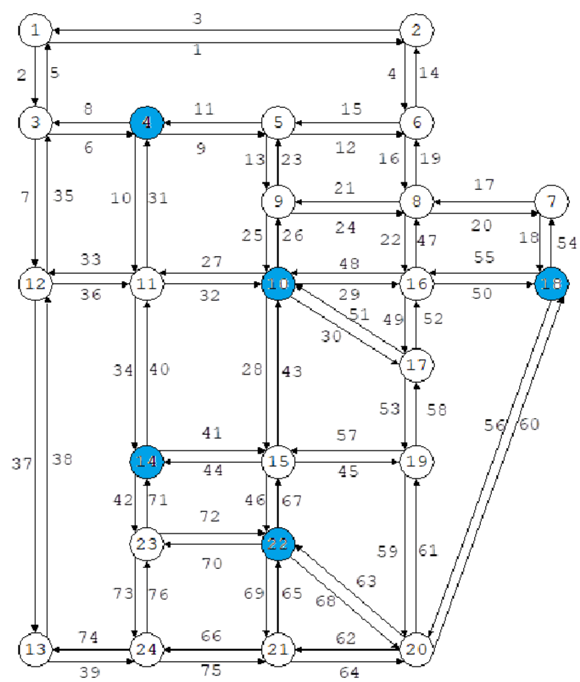
Figure 11.3 Impact of construction budget on EV market penetration rates

Next, we investigate the effect of the EV driving range on the EV market penetration and vehicle emissions rate. In this analysis, it is assumed that through the transportation agency decision-maker's policies and private sector investment, \$100,000 is allocated in each period for constructing electric charging stations. Three driving-range scenarios: 12 miles, 15 miles, and 20 miles (scenarios 1, 2, and 3, respectively). Figures 11.4 and 11.5 illustrate the impact of EV driving range on the spatial distribution of EV charging station locations and the EV market penetration rates, respectively.

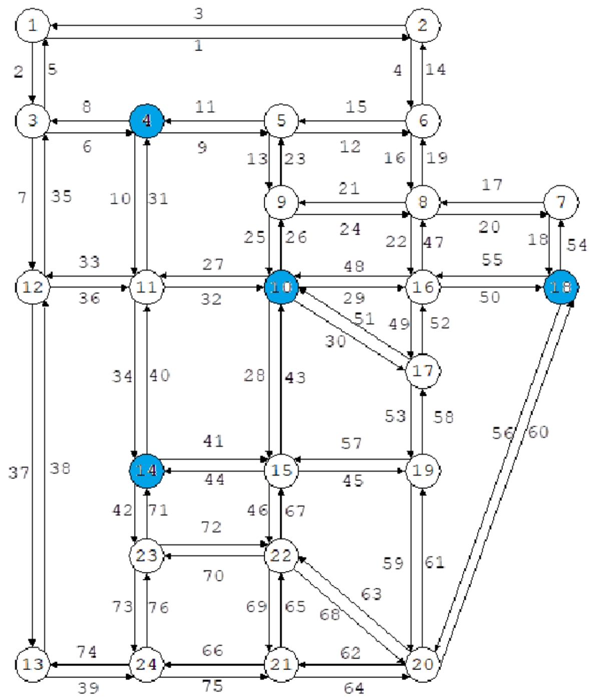
The vehicle emissions rates under driving ranges 1, 2 and 3, are 232.37 kg/hr, 217.405 kg/hr and 210.551 kg/hr, respectively. It is interesting to note that for driving range 3, fewer electric charging stations are constructed compared to driving ranges 1 and 2. Compared to the vehicle emissions rate under budget scenario 2 (209.6 kg/hr), it seems clear that with EV technological advancement (which results in higher driving range), there is reduced need for EV charging stations. Further, because recharging needs are reduced with increasing driving range, travelers can undertake their trip without deviating from their chosen or optimal routes, to recharge. Also, in this example, nodes 16 and 17 are not selected for installing electric charging stations due to higher construction costs compared to nodes with existing refueling stations.



(a) Nodes selected for EV charging stations (12-mile driving range)



(b) Nodes selected for EV charging stations (15-mile driving range)



(c) Nodes selected for electric stations (20-mile driving range)

Figure 11.4 Selected nodes under different driving range scenarios

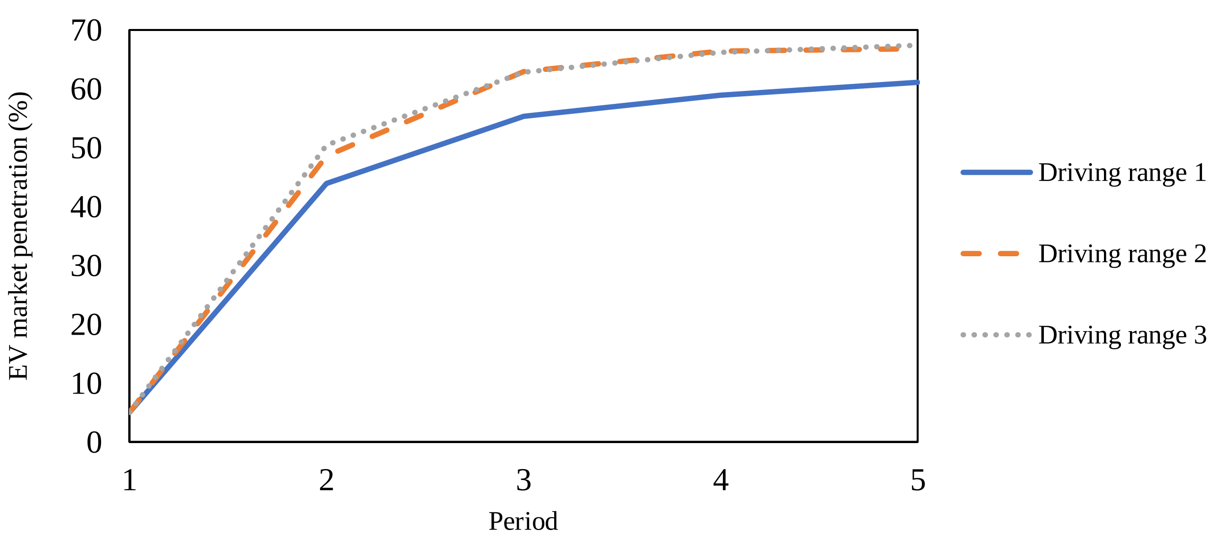


Figure 11.5 Non-linear impact of driving range on EV market penetration rates

Figure 11.6 illustrates the impact of the transition process toward the EV adoption on the average travel costs of ICEVs with refueling need. To understand the impact, we compare the travel costs of ICEV with refueling need under two cases, (i) without EVs (case 1), (ii) with EVs under budget scenario 1 (case 2) and (iii) with EVs under budget scenario 2 (case 3). Under the first scenario, the construction budget for the periods 1-5 is assumed to be $100,000 in each period. Under the second scenario, the construction budget for the periods 1-5 is assumed to be $800,000 in each period. The ICEV average travel costs are higher under case 3 compared to cases 1 and 2. The ICEV average travel time increases under cases 1 and 2. It is due to growth in travel demand during the planning horizon. Under case 3, the ICEV average travel time increases in periods 2 and 3 where it is 8 percent higher under case 3 compared to case 1 in period 3. This is because allocating a large budget to minimize vehicle emissions and promote EVs by changing existing refueling stations leads to lower accessibility to refueling stations for ICEVs. This increases their travel costs significantly compared to other cases. Under case 3, the travel cost reduces in period 5 compared to period 4 because the electric charging stations are constructed in nodes 16 and 17 without refueling stations which leads to deviation of EV travelers toward these stations which reduces the refueling travel cost of ICEVs. This analysis shows the importance of using a phased and gradual strategy for EV station investment, to be consistent with the objective of facilitating a smooth transition to EVs. A drastic and sudden reduction in the number of gas stations will increase ICEV travel costs significantly and render ICEV travel unsustainable.

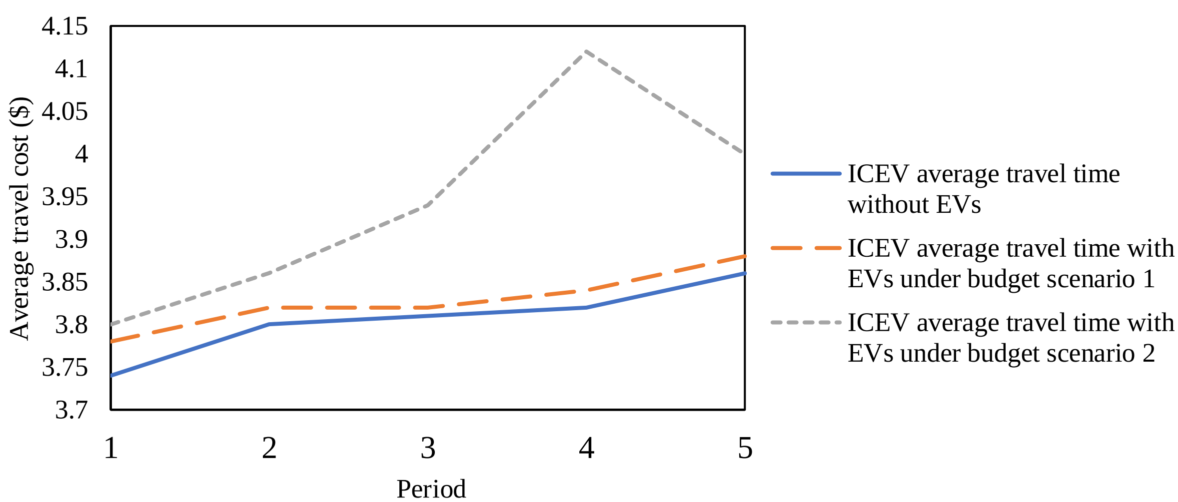


Figure 11.6 Impact of electric charging station construction budget on average travel costs of ICEVs with refueling need

CHAPTER 12 CONCLUSIONS, LIMITATIONS, AND FUTURE WORK, FOR PART II OF THE STUDY

12.1 Summary

Part 2 of this report proposed a comprehensive framework for strategically scheduling EV charging station deployments at urban areas over a long-term planning horizon within budgetary constraints, with the objective of minimizing vehicle emissions, with due consideration of travel demand. This objective is achieved through optimally locating EV charging stations and gradually repurposing the existing gasoline stations. In this framework, the transport decision-maker divides the planning horizon into multiple periods. Through agency policy and private sector initiatives fostered by the agency policy, a budget is allocated for EV charging station construction within each period. This incentivizes travelers to shift gradually from ICEVs to EVs, and (compared to an abrupt ICEV-EV shift) helps provide a smoother transition from gasoline refueling stations to electric charging stations.

The problem is formulated as a bi-level optimization model. At the upper level, the transport agency and the private sector constitute the decision maker and seek the optimal decisions regarding the number, locations, and capacities of the needed electric charging stations. At this level, the goal is to minimize the total system vehicle emissions over the planning horizon subject to budget constraints. Based on the decisions made at the upper level, travelers (at the lower level) make decisions regarding their choices of route to follow and vehicle type (ICEV vs. EV). EV travelers choose their routes with full recognition of their charging needs which depend on their driving range. A certain percentage of ICEV travelers also need to refuel per unit of time (i.e., hour, in this case) and it is assumed that they choose their routes so that they can refuel once during their trips. To capture the mode choice of travelers, this study applied the diffusion model which accounts for the influence of the net benefit earned by EV travelers in the previous period, on the EV market penetration in the subsequent period. The bi-level optimization model is solved using an active-set algorithm.

12.2 Conclusions

The numerical experiments demonstrate that if the transport decision-maker allocates sufficient budget to increase the accessibility of electric charging stations, it can significantly increase the EV market penetration and reduce vehicle emissions through the planning horizon. Further, it is demonstrated that with EV driving range increases (spurred prospectively by advances in electric battery technology), transport decision-makers will need to invest progressively smaller funds to satisfy the needs of both EV travelers' needs.

12.3 Future Work

It is possible to expand this research in several directions. This report considered only two vehicle types or “modes”: EVs and ICEVs. However, plug-in hybrid vehicles (PHEVs) (Wu et al., 2010) can recharge at electric charging stations and refuel at gasoline stations. Hence, they can play an important role in the ICEV-EV transition phase and could be considered explicitly as a separate vehicle class. Second, in this study, zero delay is assumed in the processes of refueling and charging of ICEVs and EVs, respectively. In future work, such assumption should be relaxed because currently, EV charging delay significantly exceeds ICEV refueling delay, and such difference could influence travelers’ decisions regarding their route and vehicle type choices. Finally, this study presents a solution algorithm to solve the model for the city of Sioux-Falls road network system (a relatively small network). If the framework is intended to be applied to large networks, then more efficient algorithms will need to be developed to solve the model.

Part III

CHAPTER 13 CHARGING INFRASTRUCTURE: IMPLEMENTATION AND EV FEE POLICIES

13.1 Prelude

Similar to other innovations in the course of human history, transportation automation and electrification will have both benefits and costs to transportation stakeholders including road agencies, road users, the community, and all levels of government (Labi and Sinha, 2022). The full range of costs and challenges, and the benefits and opportunities associated with the stakeholders, needs to be identified and assessed reliably before future investments can be planned with some certitude. This chapter, hopefully, throws some light on these issues.

13.2 AV-EV Synergies

There is a widespread acknowledgement by policy makers at all levels of government, automakers and technology companies, road users, and the general public that the sibling technologies of EVs and CAVs can help mitigate transportation-related societal challenges including air pollution, climate change, air pollution, traffic congestion, and travel efficiency. For this reason, it is anticipated that governments and industry will continue to make efforts to promote the deployment of both technologies in order to realize these benefits (Bagloee et al., 2016). These may proceed independently of each other or together as a synergistic duo. It is anticipated that EV market penetration will help drive CAV market penetration, and vice versa.

We now discuss a few synergies between AVs and EVs. This is based on the realization that vehicle automation is inherently conducive to electric propulsion, and electric propulsion (compared to other sources of power) is uniquely positioned to support autonomous vehicle operations. It is true that there exists a number of CAVs that use internal combustion engines (ICEs). Nevertheless, it is expected that in the future, most (if not all) CAVs will be electric. There are several justifications or reasons for this, as discussed in Labi (2022) and other sources.

- The smaller headways associated with CAV operations will require the CAV to possess the capability to quickly decelerate and accelerate as and when needed. EVs convert power into motion more efficiently compared to ICEVs (Jorgensen, 2008). EVs offer instant torque (Das & Sharma, 2022). This suggests that they are capable of rapid acceleration (is a feature generally preferred more in CAVs compared to HDVs due to CAV's greater need for collision avoidance as they are inherently more conservative (Du et al., 2021).
- The use of electric drivetrains and motors are simpler to control compared to those of internal combustion engines. This helps to reduce the complexity of the components and systems required for autonomous driving (Yi et al., 2018).
- EVs have fewer mechanical components than traditional internal combustion engine vehicles. Therefore, EVs provide greater space and opportunity for placement of sensors and other CAV-supporting hardware (Hemanth et al., 2021).

- AVs will be operating often without a driver and therefore need options for re-powering (ICEV refueling or EV recharging) that do not require a driver. ICEV refueling often requires a driver (particularly in countries and localities where gasoline is self-served and not by gas station attendants). On the other hand, EV recharging, in some cases, requires the driver to exit the vehicle to insert the plug into the socket; however, in some cases, the plug is inserted automatically without human input; or the vehicle is charged wirelessly by parking over a charging pad or along a charging guideway. For this reason, it is more beneficial for the AV to be EV rather than ICEV.
- Indications from the literature are that CAVs are likely to be operated primarily as shared vehicles. For this reason, CAVs will be required to operate for long periods of time. EVs are more amenable to long-period operations compared to ICEVs because they have fewer moving parts, require less maintenance, and are less prone to overheating.
- Future goals of transportation agencies are likely to place increased emphasis on climate change. EVs have lower emissions over life cycle (cradle to grave) compared to ICEVs, and zero emissions at tailpipe. Therefore, electrically propelled vehicles can help governments and agencies attain systemwide goals related to air quality (particularly at urban environments (Ajanovic & Haas, 2016) where air quality is a concern) and to climate change.
- Electric propulsion of CAVs is consistent with initiatives at several countries and continents that seek to migrate fully from ICEV to EVs in the next few decades. For example, the European Union plans to mandate that by 2035, all newly manufactured vehicles must emit 0 g of CO_2 (European Commission, 2022). This is also consistent with the general plans of several automakers, such as Apple, Waymo, and Tesla, to adopt electricity as the propulsion power source for future autonomous vehicles (Valdes-Dapena, 2018; Tesla, 2021; Gurman, 2021).

Therefore, while it is not strictly necessary for CAVs to be electric, there are several advantages to using electric power and making electricity a compelling choice for CAVs. A recent article on the General Motors (2022) website argued why all AVs should be EVs. As the two markets continue to evolve and mature, it is likely that their symbiotic existence and synergistic outcomes will become increasingly manifest (Seilabi et al., 2022).

13.3 Benefits and opportunities

The benefits of vehicle electrification can best be assessed vis-à-vis internal combustion engine vehicles (ICEVs) that use fossil-fuel as the energy source for propulsion. This is important because the transportation sector accounts for 27% of global greenhouse gas emissions (USEPA(a), 2022). In the era of CAVs, it is expected that the general advantages of EV will become even more apparent. These benefits include zero tailpipe emissions, generally lower net emissions over life cycle (even where cradle-to-grave impacts are considered (Hendrickson et al., 2010; Dunn et al., 2012)) compared to ICEVs, low carbon footprint and minimizing the drivers of climate change (Li et al., 2015; Peters et al., 2020). The global warming potential of EVs powered by coal-based electricity falls between those of small ICEVs and large ICEVs; and EVs powered by low-carbon energy sources or natural gas have relatively low GWP compared to even the most efficient ICEVs (Hawkins et al., 2012). In addition, unlike ICEVs, EVs do not emit carbon dioxide, particulate matter, and other noxious fumes that cause local air pollution, pedestrian discomfort, and respiratory health hazards (USEPA(b), 2022). GHG emission intensities of hybrid EVs are significantly low compared to ICEVs due to the former's higher engine efficiency (Gan et al., 2021). EVs have no engine noise and thus emit zero noise pollution. In terms of user costs, EV energy prices tend to be far more stable (lower uncertainty) compared to ICEV's gasoline prices which have a propensity to fluctuate wildly even in the short term.

Compared to ICEVs, EVs use energy more efficiently (Kirk, 2022): ICEVs typically convert into movement, only "16%-25% of the original energy goes to the wheels" (the rest is lost through conversion to heat and through other mechanical processes). For example, ICEV engines heat up quickly and require cooling systems to prevent overheating. On the other hand, EVs utilize 87-91% of their original (battery) energy into the wheels. Also, EVs possess regenerative braking capabilities (Yang et al., 2009) which recaptures and re-uses 22% of the energy produced from braking.

EVs generally have fast response, linear acceleration, and smooth power. They are less expensive to own, maintain, and operate, as they need fewer types of engine fluids (oil, transmission fluid, and coolants), fewer parts, and simpler powertrains. For these reasons, the operational or running cost of EVs is much lower than ICEVs (Milev et al., 2021). Malmgren (2016) identified EVs' social benefits (in terms of air quality human health, and the general environment) and electric grid resilience and economic growth. In the long term, transportation electrification is expected to help reduce fossil-based fuel use significantly, enhance energy security nationally, and reduce emissions thereby slowing the rate of climate change. It is useful to note that within the different modes or mechanisms for electric charging, there exist variations of the extent to which these benefits could be achieved.

13.4 Disbenefits and challenges

The success of EV charging will hinge largely on user adoption, and hence, market penetration of EVs. These will be impacted significantly by challenges associated with EV production and adoption. The challenges include the lengthy times-to-charge, battery weight, range anxiety, and low accessibility (due to inadequacy) of charging infrastructure (Chen et al., 2022). There is also the issue of the high purchase cost of EVs (in July 2022, the average EV price was approximately $18,000 higher than that of a similar traditional gasoline vehicle (Threewitt, 2022). EV prices could be lowered through subsidies (Graham and Brungard, 2022). There is also the high initial infrastructure investment cost of electric charging infrastructure. For example, the high capital and operating cost of electric guideways can pose challenges to implementation (Haddad et al., 2022). Also, it is costly to build a network of charging guideways or stations. However, if existing rights-of-way for extant gasoline refueling stations could be shared with EV charging stations, and if the charging stations are deployed in a phased manner that is consistent with EV market penetration, such high costs could be mitigated.

In terms of user costs, compared to ICEVs, EVs generally have higher initial purchase costs (but may be reduced but government subsidies as mentioned earlier in this chapter). Also, they may have lower operating costs but higher overall life cycle costs due to high purchase prices of batteries (Verma et al., 2022). Aging of the EVs' battery may lead to a higher operations cost to the vehicle owner. Also, not all EV users are able to build a charging station in their residences and may always need to recharge at public charging stations. It has been shown in the literature that new technologies such as AVs and EVs generally depreciate faster compared with more traditional vehicles; however, with increasing maturity of these technologies, their rate of depreciation is expected to decrease (Schloter, 2022).

In addition, high demand of electricity for EVs could destabilize the electric grid. This could be mitigated using market-based initiatives such as adjusting the charging rate or incentives to flatten the peak of the demand curve. Also, the issue of disposal of used batteries could be a major environmental concern in the long term, but this could be mitigated through reuse or recycling (Harper et al., 2019; Muller, 2021; Kotak et al., 2021). In cold weather, the driving range of EVs can be significantly impaired as energy is used to heat the vehicle's interior (Milev et al., 2021). In addition, EVs do not have an idling system, their recharging time far exceeds the refueling time of ICEVs, their travel distance after full recharging is generally much shorter than ICEV's travel distance after full recharging. In addition, the EVs' battery is adversely impacted in weather (temperature) extremes.

From the human health perspective, EV have higher levels of toxicity because a wider range and intensity of chemicals, metals, and energy are associated with the production of their high-voltage batteries and powertrain (Verma et al., 2022). Results from an experimental study in Japan (Takahashi et al., 2014) suggest that in a crash event, EVs do not have greater propensity to catch fire (compared to ICEVs), as the authors stated that no reason was found to treat lithium-ion battery EVs differently from ICEVs regarding mitigating the harmful gases potentially generated in case of a burning vehicle.

It has been determined that the efficacy of eco-driving initiatives applies not only to ICEVs and HEVs but also EVs. In addition, where the EV maintains a high energy-conversion efficiency at low load range, greater benefits of eco-driving could be realized compared to HEVs and ICEVs (Kato et al., 2016). The Kato et al study recognized the need to support the dissemination of strategies such as intelligent speed adaptation and traffic stabilization that encourage drivers to abide with regulation speeds in real time. They highlighted the role of AVs, in this regard, stating that with automated driving systems, trips can be accomplished with lower consumption of kinetic energy. This is yet another example of the benefits of the sibling relationship between AVs and EVs.

Also, the decommissioning of existing gasoline fuel stations to eventually pave the way for electric charging stations, will cause changes in the urban landscape (and possibly, accompanied by some social disruptions including unemployment). A more serious adverse impact of EVs is related to highway revenue: the traditional road pricing structures at most countries are based on diesel and gasoline consumption, increasing adoption will cause revenues to fall significantly (Konstantinou et al., 2022). As such, governments will need to develop alternatives pricing mechanisms for road use, including fees based on VMT, weight-distance, or electricity-usage such as $/Kw-hr of charging.

In the long term, transportation electrification may create other new environmental and social problems. These include environmental degradation, and social damage and inequity associated with the mining of specific materials such as cobalt and lithium for electric battery production (Nkulu et al., 2018) particularly in developing countries. Finally, depending on the nature of energy for production at battery plants, such production could lead to significant carbon emissions overall (Hendrickson et al., 2010; Dunn et al., 2012; Milev, et al., 2021).

Further, within the different modes or mechanisms for electric charging, there exist variations of the extent to which these disbenefits are experienced by the transportation stakeholders. For example, electric guideways provide opportunity for ubiquitous charging, and therefore help reduce or eliminate problems associated with the EV battery, such as EV range anxiety and the need for charging station infrastructure.

13.5 EV Charging Infrastructure (prospectively) for AVs

13.5.1 Introduction

Electric autonomous vehicles can be charged in one of two ways: conductive charging and contactless charging. Contactless charging can be carried out when the vehicle is stationary or when it is in motion. Table 13.1 presents EAV charging mode classifications, and Figure 13.1 presents illustration of two classes. These are discussed in greater detail in the following sections.

Table 13.1 Charging Mode Classifications

Contact status **Vehicle motion during charging**	**Conductive charging (Contact)**	**Wireless Charging (No contact)**
Static (stationary)	Yes	Yes
Dynamic (in-motion)	Yes	Yes
Quasi-dynamic (stationary and in-motion)	No	Yes

(a) Conductive charging at charging station
Photo source: https://unsplash.com/photos

(b) Contactless charging (Wireless charging) via
charging lanes. Photo source: Tim Bruns

Figure 13.1: EV Charging Mode Classifications

13.5.2 Conductive charging

EAVs can be charged conductively using a cable plugged by hand into the vehicle. This charging mode is referred to as “plug-in” charging and is commonly seen at fueling stations, parking lots, and garages. However, the term “plug-in EAV” may be considered an oxymoron because the vehicle may lack an occupant and therefore will have no way of recharging without anyone inserting the plug in the vehicle. It may be possible to use robots at recharging stations to insert the plug, but this has seen little or no discussion in contemporary literature. As such, a major limitation of conductive charging is that the charging process needs to be operated by hand. Another limitation of conductive charging is that the vehicle must be charged frequently (compared to refueling of ICVs) due to the relatively low battery capacity. In addition, in wet weather, safety issues associated with could arise. In some cases, the cable insert is permanent or intermittent, for example, at some European cities, trolley buses are recharged dynamically via a traditional form of in-motion conductive charging known as pantograph. The charging arm is supported on overhead cables, but in some cases, may jut out from the pavement beneath. It is possible (albeit, unlikely) that EAVs will be charged this way.

13.5.3 Wireless (Contactless) charging

This charging mode does not involve any contact with the vehicle and therefore is generally safer. The vehicle can be charged wirelessly when it is stationary (parked over a charging pad) or when it is in motion (charged by some guideway side infrastructure or the pavement. Chen et al. (2015) identified six main mechanisms for wireless technologies for EV charging. The first is Inductive

Power Transfer (IPT), a common example of which is the contactless charger for mobile phones. The primary limitation of IPT charging is its limited efficiency and short energy transfer distance. This could be stationary (has stringent infrastructure requirements and high costs) or dynamic (as the vehicle travels over the roadway, its onboard energy storage device receives electrical power via induction through coils embedded in the roadway pavement). Other mechanisms are: Capacitive Power Transfer (CPT), Resonant Inductive Power Transfer (RIPT), Permanent Magnet Coupling Transfer (PMPT), Resonant Antennae Power Transfer (RAPT), and On-line Inductive Power Transfer (OLPT).

13.5.3(a) The maintenance issue associated with dynamic charging.

Researchers have recognized the challenge of maintaining fragile charging components in a severe environment. Covic and Boys (2013) discussed the challenges of integrating the charging infrastructure into the roadway infrastructure. The charging infrastructure includes delicate devices including transmitters (coils and ferrite cores) and sensors. Unfortunately, these fragile materials and devices are intended to be embedded in a harsh environment (rain, ice, extreme temperatures, freeze-thaw conditions, and frequent and heavy loads) that pound the pavement. Further, the voids and relatively weak spaces within the pavement due to the embedded charging devices, render the pavement structure prone to failure and reduced longevity.

13.5.3(b) Test beds for EAV Dynamic Charging

At the current time, several ongoing field experiments on IPT integration are in progress to assess both technical and economic feasibility. For example, Konstantinou et al. (2021) designed a testbed to assess technologies for in-road EV-charging in Indiana and identified the most suitable locations for implementation. Using Interstate 65 South as a case study, their study found that direct wireless changing could be not only economically feasible for road agencies but also competitive for the EV user where EV market penetration is high. The study cautioned that the existing electric substations generally lack the capacity to fully satisfy future DWC needs. The study recommended that as EV market penetration grows, substation capacities could be expanded to support the DWC and other charging needs of EVs, and that renewable energy resources (solar and wind) could be harnessed to supplement such energy demand in a sustainable manner.

13.5.4 Quasi-Dynamic Wireless Charging (QWC)

Quasi-dynamic wireless charging represents the situation where the vehicle battery becomes charged when it is operating in stop-and-go traffic (Jang et al., 2016). This is feasible when both static wireless charging and dynamic wireless charging are available along a road corridor (Ahmed et al., 2018). At locations where dynamic charging is available, the vehicle charges wirelessly on the road; otherwise, the vehicle is charged wirelessly while in a stationary position in traffic or waiting at a signalized intersection (Mohamed et al., 2017).

13.5.5 Discussion

Patil et al. (2017) echoed the conventional wisdom that EVs can promote eco-friendly transportation but face serious limitations including battery technology issues. For example, they have low energy density (Vijayagopal et al., 2016), large weight, high cost, and key constituent materials made of rare elements). The authors argue that these limitations are mitigated by wireless charging (which reduces battery storage requirements, thereby extending driving ranges). The authors presented and evaluated the merits and demerits of dynamic wireless and stationary charging, and they reviewed the physical components, compensation networks, power electronics configurations, standards, and controls associated with each charging mode.

13.6 Economic and Policy Issues

Bansal et al. (2015) evaluated the public and residential charging infrastructure in the U.S. and provided a data-based benefit-cost analysis of three EV charging mechanisms (plug-in, wireless, and wireless charging-in-motion), accounting for factors including cost of electricity, cost of infrastructure, and overall lifetime costs. The authors argued that the infrastructure required for wirelessly charging of EVs will be lower than that of public charging stations. The authors also compared the time-of-use rates and energy-based rates for public charging and its implications and the prospective optimal policies. They also discussed common misconceptions regarding electric vehicle infrastructure and the role of federal policies and market-based mechanisms in hindering or promoting EV adoption.

Shekar et al. (2016) discussed the economics of wireless charging on the road infrastructure for a fleet of electric buses. They accounted for the bus dynamics (acceleration, rolling friction, aerodynamic drag), the lithium battery behavior, and the possibility of regenerative braking. Using simulation, the authors investigated the influence of IPT system parameters on the driving range and costs. They study estimated the detailed constituent costs of the on-road charging system components and elucidated the trade-offs between transport efficiency and on-road charging infrastructure inventory size. The authors found that the wireless on-road charging system cost exceeded that of a traditional trolley system, arguing that with increased fleet size and decreasing battery costs, it is possible in the near future, to achieve increased economic feasibility of the system.

Park et al. (2017) recognized that adequate EV charging infrastructure is indispensable for sustaining EV market penetration and analyzed the economics of on-road wireless charging. They estimated the costs of EV charging infrastructure construction, vehicle cost, and operations (including energy consumption cost). They compared the total cost associated with wireless versus plug-in charging, and determined that due to high battery costs, the user cost associated with wireless charging is generally less costly in large cities where the large expanse of wireless charging infrastructure can be used by large volumes of traffic. However, as battery prices decrease, plug-in charging will become less expensive for EVs compared to wireless charging.

Limb et al. (2016) assessed the economic feasibility of in-motion wireless power transfer (WPT) in the U.S., and showed that the overall benefits (savings) per unit vehicle exceeds the purchase cost of a WPT electric vehicle (EV). They also estimated that the societal-level payback period of the WPT infrastructure is approximately 11 years at 25% EV fleet penetration. The authors also stated that in-motion WPT satisfies 92.6% of consumers, representing a 50% higher consumer satisfaction compared to low-range EVs.

13.7 Public Acceptance

Future investments in EV charging infrastructure for EV s or EAVs, must be accompanied by assessment of public acceptance of EV and AV. Konstantinou et al. (2021) examined the public acceptance of electric roadways, and investigated the factors that affect public intention to purchase an EV and drive on electric-charging roadways in the short-term and long-term. The authors determined that EV acceptance depends on factors including the users' charging demand patterns, safety concerns regarding electric-charging roadways, and safety of commute route.

CHAPTER 14 EV CHARGING FEE POLICIES AND MECHANISMS

14.1 Prelude

This chapter discusses emerging policies and trends related to alternative fee structures to replace or complement motor fuel taxes across various states in the USA. This will continue to be an important issue in the prospective era of AVs because the inherent capabilities of AVs (such as connectivity) or the nature of AV operations, may serve to complement (or, in some cases, inhibit) the feasibility of certain charging policies and mechanisms. Charging fee policies include options such as the EV annual registration fee (discussed in Section 14.3) or the EV registration fee split into periodic payments, Pay-as-you-charge ($/kWh) for charging electric vehicles (discussed in Section 14.4) and the Vehicle per Mile Traveled (VMT) fee (discussed in Section 14.5).

14.2 Introduction

The primary funding for transportation has depended heavily on the revenue generated from motor fuel taxes. With the introduction of vehicle connectivity, automation, and electrification, the transportation landscape continues to evolve, with continual enhancements in fuel efficiency. The emerging vehicle technologies, unfortunately, are accompanied by higher needs and infrastructure expenditures yet declining revenue streams (due to higher fuel efficiencies or non-gasoline fuels that will characterize CAVs). Also, there exist equity concerns and challenges associated with tax or fee collection efficiency and effectiveness. Specifically, the challenges and issues associated with alternative fuels and advanced vehicle technologies include:

- Improved vehicle fuel efficiency driven by technology and updated EPA regulations.
- Bias in road-use tax due to exempt status of certain vehicle types that do not use fossil fuel for propulsion.
- Implementation of stricter vehicle emission standards.
- Variations in vehicle weights and classifications that preclude estimation of infrastructure damage contributions.
- Differences in measures and policies between state and federal agencies.

The possibility of EV charging at locations other than conventional recharging/refueling stations (such as, at residences or workplaces) is a significant consideration. Legislators and regulators at several states continue to update highway revenue structures to include alternative fuel use. This helps compensate for revenue reductions resulting from improved vehicle efficiency and the growing transition from gasoline fuel to electrification. The discussions below offer an overview of proposed strategies to address these challenges. To offset the decline in fuel tax revenue due to the increasing use of EVs, highway agencies have primarily adopted a methodology involving estimating an annual supplemental fee per EV. This fee is calculated to balance the loss in fuel tax revenue associated with the growing market penetration of EVs (referred to as the "recovery EV fee"). Figure 1 (Konstantinou et al., 2022) presents the calculations for this.

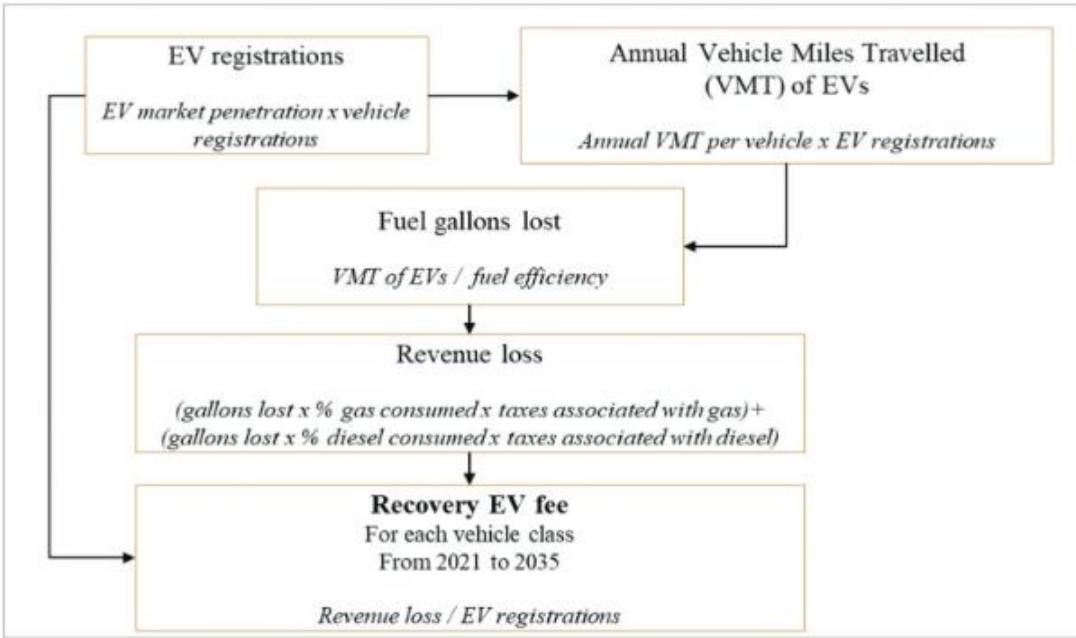


Figure 14.1 Methodology to calculate recovery EV fee (Konstantinou, et al., 2022)

It is anticipated that such fees, however, might adversely impact EV market penetration. Taxing EVs differently has often been met with resistance, considering that they are considered preferable to traditional gas-powered vehicles (from an environmental viewpoint) and they produce lower adverse impacts on the environment. Therefore, the alternative approaches to implementing the recovery EV fee need to ensure both sufficient revenue generation and support for EV adoption. For example, vehicle weight and classification need to be considered in EV fee design. The approaches used in various states are discussed below.

14.3 EV annual registration fee

The annual registration fee method involves collecting the entire EV recovery fee on an annual basis from the EV users. These fees are linked to vehicle ownership, making them a dependable revenue source in comparison with usage-based fees because it is anticipated that vehicle ownership will not decline significantly at least not in the short term. This approach, adopted by most states, aligns with the existing system of registration revenue generation, and consequently requires less educational outreach and public awareness effort and is more cost-effective to implement. However, the primary drawback here is the requirement to pay the recovery fee upfront, which will be burdensome for some users. Therefore, unless a phased payment format is adopted, this approach could potentially hinder EV adoption, particularly among heavier vehicle classes. To alleviate the burden of high upfront fees, offering periodic payments such as monthly or quarterly options, or, pay as you charge (PAYC), could be considered.

The current trends adopted in the states show that as of February 2022, thirty-one (31) states have passed EV-fee related legislation and established EV annual fees (TIAC, 2022a). Typically, the EV annual fee applies to all classes of EVs including plug-in hybrids, from $50 (in Colorado, Hawaii, and South Dakota) to $235 (indexed fee, in Michigan). The state of Utah has an annual charge of $120 per vehicle and has an optional road user charge program, along with a fee on charging stations. Table 14.1 presents the fees across some states as of February 2022.

14.4 Pay-as-you-charge ($/kWh)

In this approach, the EV recovery fee is transformed into an excise tax on electricity used for charging EVs at a retail location, measured in dollars per kilowatt-hour ($/kWh). This method is similar to the traditional fuel tax payment mechanism (pay-at-the-pump), making it more user-friendly and easier for agencies to implement. The fee can be collected efficiently at a small number of transaction points. However, there exist significant challenges associated with this mechanism. Charging mostly occurs at the residence, and therefore could be challenging and expensive to differentiate between residential electricity consumption and EV electricity usage. Monitoring of the EV residence charging can be difficult, and residents may be reluctant to pay taxes for residential charging of their EV. Similarly, imposing a tax on workplace charging could be problematic, particularly where workplaces or public locations offer free charging, impairing the establishment of a clear transaction point for the tax payment. Besides tracking-related difficulties, this approach raises privacy concerns and requires the installation of expensive equipment.

In addition, fees based on electricity consumption may not reflect vehicle weight, and therefore unable to adequately account for variations in the damage causes by different classes of vehicles. Admittedly, heavier vehicles generally consume more kWh/mile. To implementing this approach, submetering or smart chargers, and on-vehicle technology will be needed to measure the electricity consumption attributable to the EV in a reliable manner. The utilities companies would need to create novel tariff structures to incentivize specific charging behaviors including charging times (off-peak, on-peak) as these could lower EV users charging costs and promote EV adoption. Also, it has been argued in the literature that it will be useful for stakeholders to establishing linkages among the utility companies, state and local DOTs and other agencies, and government regulators. Past researchers have stated that doing this could facilitate charging-related payment transfers to revenue collection agencies, particularly in the case of residential charging.

As of July 2022, four states had established a per-kilowatt-hour excise tax on electric vehicle charging (TIAC, 2022b): Oklahoma, Iowa, Pennsylvania, and Kentucky. In Oklahoma, starting from January 1, 2024, a three-cent tax per kilowatt-hour will be imposed on electric vehicle charging, along with registration fees based on vehicle weight and type. Iowa introduced a hydrogen fuel excise tax effective from January 1, 2020, and initiated a per-kilowatt-hour excise tax on electric power starting July 1, 2023. In Pennsylvania, as of 2022, the excise tax rate on electric power stands at 1.72 cents per kilowatt-hour. Kentucky has implemented a per-kilowatt-hour excise tax on electric vehicle power, beginning January 1, 2023, at a rate of 3 cents per kilowatt-hour. Table 14.2 summarizes the pay-as-you-charge fees used in some states.

Table 14.1 Annual Registration Fee of EVs in various states

State	EV Fee	Hybrid Vehicle Fee	Frequency
Alabama	$200	$100	Annual
Arkansas	$200	$100	Annual
California	$100 (Indexed)		Annual
Colorado	$50		Annual
Georgia	$200 / $300		Annual
Hawaii	$50		Annual
Idaho	$140		Annual
Illinois	$100		Annual
Indiana	$150 (Indexed)	$50 (Indexed)	Annual
Iowa	$130	$65**	Annual
Kansas	$100	$50	Annual
Kentucky*	$120	$80	Annual
Michigan	$135 - $235 (Indexed)	$47.50 - $117.50 (Indexed)	Annual
Minnesota	$75		Annual
Mississippi	$150 (Indexed)	$75 (Indexed)	Annual
Missouri	$75 - $1,000	$37.50 - $500**	Annual
Nebraska	$75		Annual
North Carolina	$130 (Indexed)		Annual
North Dakota	$120		Annual
Ohio	$200	$100**	Annual
Oklahoma*	$120		Annual
Oregon	$110		Annual
South Carolina	$120	$60	Biennial
South Dakota	$50		Annual
Tennessee	$100		Annual
Utah	$120 or RUC (Indexed)	$62 (Indexed)	Annual
Virginia	85% of gas tax equivalent	85% of gas tax equivalent	Annual
Washington	$150	$50**	Annual

1

West Virginia	$200	$100	Annual
Wisconsin	$100	$75	Annual
Wyoming	$200		Annual

Table 14.2 Pay-as-you-charge excise tax at various states.

State	Pay-as-you-charge ($/kwh)
Oklahoma	3.00 cents
Iowa	2.60 cents
Pennsylvania	1.72 cents
Kentucky	3.00 cents

14.5 Vehicle per miles travelled fee (VMT Fee)

The VMT fee ($/mile), also known as the Road Usage Charge (RUC), is a user fee that is based on the distance driven by a vehicle (March, 2005; Oh et al., 2007; Rodrigues and Pulugurtha, 2021). A significant advantage of the VMT fee is its facilitation of fee payments to be spread across time (for example, months), thereby prospectively easing any financial burden on users. However, it is cautioned that these fees may not accurately reflect the impact of each user group (for example, vehicle class) on the road system. They might also discourage the use of electric vehicles (EVs) for relatively long distance trips and therefore may not receive consistent levels of acceptance across urban and rural drivers. In addition, privacy concerns may arise because of the way the distances traveled are monitored. Further, administrative costs could be rather high due to the use of monitoring technologies, transaction charging systems, and online account management. A well-designed system should consider potential inequities (for example, the disparities between rural and urban EV users) and could be made to incentivize behavior that enhances fuel efficiency. It has been argued by certain proponents that EVs generally deserve to have lower VMT fees compared to HDVs because they contribute to improved air quality and lower emissions overall. However, it is important for any VMT fee structure to generate commensurate revenue for highway transportation needs. Combining VMT fees with weight-based fees could help establish more equitable fee structures that also account for EV impacts on the road. Some researchers have argued that mileage-based fees are generally closer to accounting for externalities and to measurement of each user's road expenditure cost responsibility.

As of July 2022, three states—Virginia, Utah, and Oregon—had in place fully operational RUC programs. Utah's RUC program fee is 1.52 cents/mile that goes towards a "Road Usage Charge Program Special Revenue Fund," capped at the flat registration fee in the state. In Oregon's OReGO program, participants pay 1.8 cents/mile fee in lieu of the state's motor fuel tax, and participants receive credit. Virginia's "Mileage Choice Program" serves as an alternative to its "Highway Use Fee," which has a fixed annual rate on EVs and fuel-efficient vehicles. Participants of the Mileage Choice option forego the use fee. Their $/mile rate is calculated based on the average number of miles driven annually (approximately 11,600 miles) and is limited to what they would have paid for the HUF. Connecticut has a dedicated program for commercial trucks (TIAC, 2022c). Also, some other states are either have pilot programs or are conducting studies in this regard. Table 14.3 presents the various levels of state's VMT fees.

Table 14.3 VMT Fee implemented in various states.

State	VMT Fee (per mile)
Oregon	1.8 cents
Utah	1.52 cents
Virginia	Rate equivalent to highway use fee

14.6 Concluding comments

Numerous states are currently engaged in discussions on alternative revenue sources to address imminent shortfalls in highway funding, a clear and present threat driven by the declining revenues from motor fuel taxes. These discussions are occurring against the background of a nationwide trend of growing electric vehicle (EV) adoption. This trend holds particular significance because the states rely heavily on gas taxes and registration fees as the primary means of funding their highway infrastructure. Concurrently, there are ongoing discussions at the federal level regarding highway funding adequacy or tax/fee collection methods. The Infrastructure Investment and Jobs Act (IIJA) proposed the establishment of a national pilot program for road usage fee even as it continued to support pilot initiatives by individual states. The "National Motor Vehicle Per-Mile User Fee Pilot," authorized by the IIJA with a budget allocation of $50 million over five years, is intended to evaluate various aspects (including financial sustainability, acceptance, implementation) and is expected to culminate in recommendations regarding the implementation of the concept.

From a policy perspective, a number of initiatives have been discussed in the literature. It is critical to develop realistic and equitable plans to address the problem of declining revenue from fuel taxes, particularly, as the transportation system transitions toward EV technologies and alternative fuels. It has been recommended that policymakers must exercise caution in setting timelines for these alternative approaches. Threats to plan success include imbalances that make EV ownership more expensive compared to an ICEV vehicle and thereby hinder EV adoption. Additionally, potential barriers to implementation should address concerns related to sustainability, costs, and privacy. Policy considerations should involve implementation processes, partnerships, and equity. Further, the distribution of fee collection deserves due consideration, given that gas purchases typically occur on a weekly or bi-weekly basis. From a broader perspective, as the gap between overall highway revenues and highway expenditures continue to widen, and as EV growth threatens to exacerbate this gap, overall strategies to address this conundrum are needed. Initiatives and progressive approaches are needed to recover the loss of fuel-tax based revenues. Such initiatives include the VMT fee, weight-distance fee, raising the gas tax, and indexing the gas tax to inflation. Consideration of these initiatives are currently ongoing at various levels of government – federal, state, and local – and resolution is needed soon, to ensure a sustainable and fair funding model for the evolving transportation landscape.

Part IV

CHAPTER 15 OVERALL CONCLUDING REMARKS

This chapter summarizes the three parts of this report, highlights their significance, provides some concluding comments, and suggests directions for future research. Section 15.1 summarizes the research and discusses associated conclusions. Section 15.2 highlights the significance of the research from theoretical and practical perspectives. Section 15.3 discusses possible extensions and directions for future research.

15.1 Research summary

Part 1 of this study provided a comprehensive framework to determine the locations of charging facilities (stations or guideways) to serve HDVs and AVs. The framework is formulated as a bi-level program where transportation decision-makers seek to minimize the total travel time, and the travelers seek to minimize their travel time. The decision variables are the locations of EV charging facilities subject to budgetary limitations. The study demonstrated the framework using the Sioux-Falls network. The numerical experiments suggest that, compared to the scenario where the transport decision-makers provide charging stations only or wireless-charging lanes only, the scenario where both facilities are provided causes reduction in the total travel time cost by 82% and 3%, respectively. It is also shown that providing wireless-charging guideways at both AV-exclusive and general-purpose lanes can cut the total travel time by 25% and 36% compared to plan where wireless-charging guideways are provided only at AV-exclusive lanes and where they are provided only at general-purpose lanes, respectively.

Part 2 of this study presents a proposed framework for scheduling EV charging station deployments and repurposing existing gas stations within a long-term planning horizon and a specified budget with the goal of minimizing vehicle emissions. Through agency policy and private sector initiatives fostered by the agency policy, a budget is allocated for EV charging station construction within each period. The transport decision-maker and the private sector make the optimal decisions regarding the number, locations, and capacities of the needed EV charging stations, in a bid to minimize emissions. Based on this, travelers choose their routes and vehicle types (EV vs. ICEV). EV travelers choose their routes with full recognition of their charging needs which depend on their driving range. The numerical experiments measure the sensitivity of accessibility of EV charging stations (and hence, the EV market penetration) to EV infrastructure spending. Further, the study demonstrated the extent to which technological advancements and anticipated increases in the EV driving range will cause progressively lower need for EV charging infrastructure.

Part 3 of the report discussed the implementation issues, challenges, and opportunities associated with EV-charging infrastructure for autonomous vehicles. This part addresses the AV-EV synergies and explains why they constitute a symbiotic pair, the benefits, and opportunities of EAVs, and the disbenefits and challenges associated with EAVs. This part also discusses various

EV charging infrastructure based on the charging modes and mechanisms. Finally, the economic and policy issues, public acceptance, and EV charging fee considerations are discussed.

15.2 Research contributions

Part 1 of the study provided a planning framework for EV charging facilities during the AV transition phase. This framework optimizes EV charging facility types, locations, and capacities while accounting for the actions and perspectives of the agency (such as, EV charging facility investment) and users (i.e., travel time minimization). The proposed framework throws light on the impacts of EV investment levels on AV market penetration and the impacts of installing wireless-charging facilities on GP and AV-exclusive lanes on travelers' route and vehicle type choices. The contributions of this research are threefold. First, it addresses optimal location of EV charging facilities considering a mixed fleet (AV and HDV). Second, it considers the possibility of EVs to be recharged at both wireless charging guideway as well as charging stations during a single trip. Third, it considers the possibility of installing wireless charging facilities at both AV-exclusive lanes and general-purpose lanes.

In Part 2 of this study, there are four major contributions to literature. First, it considers ICEV refueling needs as part of the phased-transition plan toward fully adopting EVs over a planning horizon. Therefore, this study considers both brownfield development (gradual conversion of existing gas stations to electric charging stations) and greenfield development (deploying new charging stations to meet the energy demand) and considers possible decommissioning of existing gas stations, as the second contribution. This raises important equity issues, given the generally higher prices of EVs compared to HDVs. Third, this study considers vehicle emissions as the objective function of EV charging station construction framework. Fourth, in developing the EV charging station decisions, this study considers two key aspects related to the expected advancements in electric charging technology over the planning horizon: EV driving range and EV extra ownership cost. The study does this by considering growth in EV driving range over the planning horizon. Next, the study duly considers the time-dependent additional cost of EVs relative to ICEVs because the EV purchase cost is expected to reduce over time due to technological advancement and scale economies of EV production. Finally, the study acknowledges that any framework for designing an EV charging network should: (i) meet the changing needs of a growing number of EV consumers, (ii) address the refueling needs of ICEV consumers over the long-term, (iii) be capable of translating the specific impact of charging infrastructure availability on EV market adoption over the planning horizon.

15.3 Study limitations and future research directions

The findings of Part 1 of the study provide some directions for future research. First, this study investigated the impacts of AV-exclusive lanes whose locations were assumed to be fixed in this study. Future research could develop a model that considers variable locations of AV-exclusive lanes. Next, future research could consider that the impacts of privately-owned AVs may not be the same as that of shared AVs. Finally, battery swapping can be considered as a third option for EV charging.

The research carried out in Part 2 of the report can be extended in several directions. First, this report considers only ICEVs and EVs. However, plug-in hybrid vehicles (PHEVs) can recharge at electric charging stations or refuel in gas stations. Hence, they can play an important role in this transition phase toward EVs and therefore could be considered in any such study. Second, this study assumes zero delay for charging and refueling of EVs and ICEVs, respectively. However, this assumption needs to be relaxed in future studies as the charging delay of EVs currently is significantly higher compared to the refueling delay of ICEVs, and this could influence the travelers' route and vehicle type choices. Finally, this study develops a solution algorithm to solve the optimization model for the Sioux-Fall city network. More efficient algorithms will be needed to solve the model if it is to be applied to larger networks.

CHAPTER 16 SYNOPSIS OF PERFORMANCE INDICATORS

16.1 Part I of USDOT Performance Indicators

Over the study period for this project, three (3) transportation-related courses were offered that were taught by the PIs. One of the courses had a teaching assistant who is also associated with this research project. Four graduate students and a post-doctoral researcher participated in the research project during the study period. During the study period, one (1) transportation-related advanced degree (doctoral) program and one (1) transportation-related M.S. program utilized the CCAT grant funds from this research project to support the graduate students. The fourth graduate student was a self-funded M.S. student who worked on this project for one year. Two of the M.S. students graduated in December 2020 and August 2021, and the third MS student is set to graduate in August 2023. The post-doctoral researcher who is a co-PI of this study, was appointed a tenure-track faculty member at the Illinois Institute of Technology in Chicago.

16.2 Part II of USDOT Performance Indicators

Research Performance Indicators:
Two (2) journal publications and three (3) conference presentations were produced from this project. The research from this advanced research project was disseminated to over 90 people in attendance (from industry, government, and academia) through the 3 conference presentations. These include the Purdue Road School (2022), and the Transportation Research Board's 99th and 100th Annual Meetings held in Washington, D.C. in 2020 and 2021 respectively.

Leadership Development Performance Indicators:
This research project generated 3 academic engagements and 2 industry engagements. The PIs held positions in 2 national organizations that address issues related to this research project. One of the CCAT students who worked on this project holds a membership position in a related ASCE committee related to the subject of this research. The post-doctoral researcher holds a position in a TRB committee related to the subject of this research.

Education and Workforce Development Performance Indicators:
The methods, data and/or results from this study were incorporated (or are being incorporated) in the syllabi for the Spring 2021, Fall 2021, Spring 2022, and Fall 2022 versions of the following courses at Purdue University:
(a) CE 561: Transportation Systems Evaluation, a mandatory graduate level course at Purdue's transportation engineering graduate programs (average 12 students at each course offering),

(b) CE 299: Smart Mobility, an optional undergraduate level course at Purdue' civil engineering B.S. program, (average 12 students),

(c) CE 398: Introduction to Civil Engineering Systems, a mandatory undergraduate level course at Purdue University's civil engineering program, (average 85 students at each course offering).

These students will soon be entering the workforce. Thereby, the research helped enlarge the pool of people trained to develop knowledge and utilize at least a part of the technologies developed in this research, and to put them to use when they enter the workforce. Based partly on a recognition of his contributions to this study, the post-doctoral researcher on this project earned a faculty position at the Illinois Institute of Technology.

The methods, data and/or results from this study will also be incorporated in future versions of the courses stated above.

Collaboration Performance Indicators:

There was collaboration with other agencies, and 1 agency and 2 institutions provided matching funds. The CCAT PI collaborated with various professors at Purdue and outside Purdue on an Indiana DOT-funded project related to this study, titled "A Strategic Assessment of Needs and Opportunities for the Wider Adoption of Electric Vehicles in Indiana, under SPR 4509.

Collaborated with Professors Donghui Chen, Kyubyung Kang, C Koo, Cheng Peng, Konstantina Gkritza, on the INDOT-funded project. The outcome of the collaboration was a research report and 2 journal papers.

Collaboration report: A Strategic Assessment of Needs and Opportunities for the Wider Adoption of Electric Vehicles in Indiana, by Konstantinou, T., Chen, D., Flaris, K., Kang, K., Koo, D. D., Sinton, J., Gkritza, K., & Labi, S. (2020).

Collaboration paper: Agent-Based Model of Electric Vehicle Charging Demand for Long-Distance Driving in the State of Indiana, by Chen, D., Kang, K., Koo, D. D., Peng, C., Gkritza, K., & Labi, S. (2022), Transportation Research Record, 2677(2).

The outputs, outcomes, and impacts are described in Chapter 17.

CHAPTER 17 STUDY OUTCOMES AND OUTPUTS

17.1 Outputs

17.1.1 Publications, conference papers, or presentations (from major conference or similar event)

<u>(a) Publications</u>

Guo, Y., Souders, D., Labi, S., Peeta, S., Benedyk, I., Li, Y. (2021). Paving the way for autonomous Vehicles: Understanding autonomous vehicle adoption and vehicle fuel choice under user heterogeneity, Transportation Research Part A: Policy and Practice 154(1), 364-398. *https://www.sciencedirect.com/science/article/pii/S0965856421002731*

Pourgholamali, M., Correia, G., Tabesh, M.T., Seilabi, S.E., Miralinaghi, M., and Labi, S. (2023). Robust Design of Electric Charging Infrastructure Locations under Travel Demand Uncertainty and Driving Range Heterogeneity. *ASCE Journal of Infrastructure Systems* 29(2), 04023016-1. *https://ascelibrary.org/doi/full/10.1061/JITSE4.ISENG-2191*

<u>(b) Conference Proceedings</u>

Miralinaghi, M., de Almeida Correia, G.H., Seilabi, S.E., Labi, S. (2020). Designing a Network of Electric Charging Stations to Mitigate Vehicle Emissions, in: 2020 Forum on Integrated and Sustainable Transportation Systems, Institute of Electrical & Electronics Engineers (IEEE), Delft, Netherlands, pp. 95–100. *https://doi.org/10.1109/fists46898.2020.9264883*
Link where published: https://ieeexplore.ieee.org/document/9264883

<u>(c) Presentations</u>

Miralinaghi, M., Correia, G., Seilabi, S.E., and Labi, S. (2020). Minimizing Urban Vehicular Emissions Through the Efficient Design of Electric Charging Station Network, 2nd Next Generation Transportation Systems Conference, W. Lafayette, IN.

Miralinaghi, M., Tabesh, M.T., Correia, G., Seilabi, S.E., Davatgari, A., and Labi, S. (2021). Robust Design of Electric Charging Locations under Travel Demand Uncertainty, 100th Annual Meeting of the Transportation Research Board, Washington, D.C.

Pourgholamali, M., Correia, G., Seilabi, S.E., Miralinaghi, M., and Labi, S. (2022). “Robust Design of Electric Charging Locations under Travel Demand Uncertainty and Driving Range Heterogeneity,” Purdue Road School, March 2022, West Lafayette, IN

17.1.2 Other outputs

<u>(a) Editorials for Technical Journals</u>

The CCAT PI and co-PI of this study, and two cost-share collaborators served as guest editors of a special issue in the *Frontiers in Built Environment* journal, where they edited a collection of articles on automation, connectivity, and electric propulsion. Their special journal issue joint editorial is published with the following citation:

Labi, S., Anastasopoulos, P., Miralinaghi, M., Ong, G.P., Zhu, F. (2021). Editorial: Advances in Planning for Emerging Transportation Technologies: Towards Automation, Connectivity, and Electric Propulsion, Frontiers in Built Environment 7, 666246. *https://www.frontiersin.org/articles/10.3389/fbuil.2021.666246/full*

(b)Policy Papers, Patents, etc.

One EV policy paper has been produced from this research, and website is being developed for the outcomes of this research. The research produced (a) a methodology for determining the locations of EV charging facilities (stations or guideways) to serve a mixed fleet of HDVs and AVs, and (b) a new methodology for strategically scheduling EV charging stations over a long-term planning horizon and a specified budget, including decommissioning exiting gas stations and/or converting them to charging stations as EV market penetration grows.

No patents have yet been filed for the research outcomes. The research outcome (framework, methodology, analytical models, and case study) has been used in Purdue University's undergraduate and graduate courses related to electric transportation, vehicle automation, and infrastructure preparation towards EV or AV operations.

(c) Student Theses

Davatgari, A. (2021). Location planning for electric charging stations and wireless facilities in the era of autonomous vehicle operations, M.S. Thesis, Purdue University, West Lafayette, IN. *https://docs.lib.purdue.edu/dissertations/AAI30504864/*

Pourgholamali, M.H. (2022). Robust design of electric charging infrastructure locations under travel demand and driving heterogeneity, M.S. Thesis, Purdue University, W. Lafayette. *https://hammer.purdue.edu/articles/thesis/Robust_Design_of_Electric_Charging_Infrastructure_Locations_under_Travel_Demand_Uncertainty_and_Driving_Range_Heterogeneity/24878361*

17.2 Outcomes

This project produced outcomes that could influence road agencies' transportation system design or operational policies. These are:

- Increased understanding and awareness of the impacts of growing demand of electric AVs on the infrastructure to support these and other next-generation transportation technologies,
- Consideration of the methodologies and frameworks developed in this study for long-term infrastructure needs and related planning functions,
- More reliable and robust long-term infrastructure planning (by urban road agencies) that accounts for vicissitudes on the highway transportation terrain including the emergence of advanced technologies including vehicle electrification with automation,

- Enhanced overall infrastructure adequacy and road-users' travel efficiency at large urban networks in the prospective era of electric AVs.

17.3 List of impacts

The impacts of this project are expected to be manifest through the effects of its outcomes on the transportation system, or society in general, such as reduced fatalities, decreased capital or operating costs, community impacts, or environmental benefits. This includes how the research outcomes can potentially improves the operation and safety of the transportation system, increase the body of knowledge and technologies, enlarges the pool of people trained to develop knowledge and utilize new technologies and put them to use, and improve the physical, institutional, and information resources that enable people to have access to training and new technologies. A list of specific impacts from this research project, are as follows:

- Support for electricity as the preferred choice of AV propulsion. Electric propulsion has advantages including reduction on foreign sources for energy (and subsequently, enhanced national security), a net impact of cleaner air and lower impact on climate, reduced cost of vehicle operations, and reduced traffic noise.
- Strategic location of charging lanes and stations resulting in reduced congestion in a road corridor or a network in the era of electric AVs. The decision support frameworks are geared primarily towards (as much as possible) reducing the travel time of road users in the AV dedicated lanes as well as those in the general-purpose lanes.
- Stronger justification for highway agencies to make investments (or to make policies that incentive the private sector to make) as part of preparations for the CAV era in terms of EV infrastructure provision. We expect that the research, when applied in the practice, will provide proof that such infrastructure investments can and will greatly benefit the entire society in terms of the social, economic, and environmental impacts of EAVs.
- The graduate students that worked on this project will enter the workforce in 2023 and 2024 to help support the workforce that will implement new technologies such as those developed in this study.
- The project had impact on education, as parts of the research outcomes were incorporated in two undergraduate and one graduate level courses at Purdue University. These students, who will soon be entering the workforce, benefitted from the outcomes of this research through these academic platforms. This helps enlarge the pool of people trained to develop knowledge and utilize the technologies developed in this research, and to put them to use when they enter the workforce.

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APPENDIX 1

CCAT Project: Facilitating Electric Propulsion of Autonomous Vehicles through Efficient Design of a Charging-Station Network

Published Related Work

Pourgholamali, M., Correia, G., Tabesh, M.T., Seilabi, S.E., Miralinaghi, M., and Labi, S. (2023). Robust Design of Electric Charging Infrastructure Locations under Travel Demand Uncertainty and Driving Range Heterogeneity, Journal of Infrastructure Systems 29(2), https://ascelibrary.org/doi/full/10.1061/JITSE4.ISENG-2191

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Abstract

The rising demand for electric vehicles (EVs), motivated by their environmental benefits, is generating an 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. Such investment decisions, which include EV charging station locations and capacities, and the timing of such investments require robust estimates of future travel demand and EV battery range constraints. This paper develops and implements a framework to establish an optimal schedule and locations for new charging stations and decommissioning gasoline refueling stations over a long-term planning horizon, considering the uncertainty in future travel demand forecasts and the driving range heterogeneity of EVs. A robust mathematical model is proposed to solve the problem by minimizing not only the worst-case total system travel cost but also the total penalty for unused capacities of charging stations. This study uses an adaptation of the cutting-plane method to solve the proposed model. Based on two key decision criteria (travelers' cost and charging supply sufficiency), the results indicate that the robust scheme outperforms its deterministic counterpart.

Guo, Y., Souders, D., Labi, S., Peeta, S., Benedyk, i., Li, Y. (2021). Paving the way for autonomous Vehicles: Understanding autonomous vehicle adoption and vehicle fuel choice under user heterogeneity, Transportation Research Part A: Policy and Practice 154(1), 364-398. https://www.sciencedirect.com/science/article/pii/S0965856421002731

Abstract

Vehicle automation, along with vehicle electrification and shared mobility, may transform the existing transportation if they are handled properly. However, they may create unintended consequences if the current market dominance of fossil fuel and privately-owned vehicles persists, and travel patterns and transportation policies remain unchanged. The extent of these potential benefits and unintended consequences depends on the expected AV adoption process, people's preferred vehicle powertrain, and AV-related policy and infrastructural support. This paper seeks to understand the impacts of attitudinal factors and roadway designs on people's intention to use AVs and to purchase battery-electric AVs (EAVs) and gasoline-powered AVs (GAVs) under travel and user heterogeneity. Fourteen latent attitudinal factors related to the perceptions and attitudes towards AV and EV technologies, driving, the environment, and personal innovativeness were considered. An EAV-enabled urban design environments were created, featuring dedicated AV lanes, wireless charging for EAVs, and AV pick-up/drop-off zones. Using a stated preference survey data of over 1300 responses in the U.S., Multiple Indicators and Multiple Causes models are estimated to understand the relationship among various latent variables and capture heterogeneities within the population based on their sociodemographic and behavioral characteristics. The model estimation results show that the respondents' perception of AVs and EAVs advantages, road safety improvement potential, compatibility with their lifestyles and travel needs, and their attitudes towards driving are key factors of their intention to use AVs and purchase EAVs. Furthermore, some segments of the population based on their sociodemographic and travel behavior characteristics are more likely to have a higher intention to use AVs and buy EAVs. The model estimation results, and study insights can be used by policymakers to develop road network design guidelines and policies to nudge consumers towards more sustainable transportation options, minimize the unintended consequences of vehicle automation, and maximize its benefits.