# LOCATION PLANNING FOR ELECTRIC CHARGING STATIONS AND WIRELESS FACILITIES IN THE ERA OF AUTONOMOUS VEHICLE OPERATIONS

by

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*Dedicated to my beloved parents Nahid and Mohammad.*

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# TABLE OF CONTENTS

# LIST OF TABLES

## LIST OF FIGURES

# NOTATIONS

| **Sets** | **(Network features)** |
|---|---|
| $\boldsymbol{N}$ | 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 (Specified model inputs)**

| | |
|---|---|
| $\boldsymbol{B}$ | Construction budget, $ |
| $\boldsymbol{W}$ | Users' average wage rate, $/hr. |
| $\boldsymbol{Y}$ | Average vehicle longevity, years |
| $\boldsymbol{t_{0,ij}}$ | 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 |
| $\boldsymbol{\gamma_k^1}$ | Capacity of Level 1 charging station at candidate node $k$, veh/hr |
| $\boldsymbol{\iota_0}$ | Variable-cost component of a charging station construction, $ |
| $\boldsymbol{\iota_1}$ | Fixed-cost component of a charging station construction, $ |
| $\boldsymbol{\pi_0}$ | Variable-cost component of wireless-charging facility construction, $/mile |
| $\boldsymbol{\pi_1}$ | Fixed-cost component of wireless-charging facility construction, $ |
| $\boldsymbol{\varsigma}$ | Capacity level category of station with maximum charging capacity level, veh/hr |
| $\boldsymbol{\beta_0}$ | Weight of vehicle purchasing price in the utility function |
| $\boldsymbol{\beta_1}$ | Weight of total travel cost in the utility function |
| $\boldsymbol{\bar{R}}$ | Maximum driving range of vehicles, mile |
| $\boldsymbol{\bar{\bar{R}}}$ | Initial driving range of vehicles, mile |
| $\boldsymbol{C_v}$ | Purchasing price of EV type $v$, $ |
| $\boldsymbol{\xi}$ | Weight of agency (construction) cost relative to user (delay) cost |

**Variables**

| | |
|---|---|
| $\boldsymbol{Z^U}$ | Objective function for the upper-level problem (the transportation agency's decision maker) |
| $\boldsymbol{Z^L}$ | Objective function for the lower-level problem (the travelers' decision) |
| $\boldsymbol{\phi_1}$ | Cost of total system travel time, \$ |
| $\boldsymbol{\phi_2}$ | Total construction cost of charging facilities, \$ |
| $\boldsymbol{t_{ij}}$ | 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 $k$, $y_k \in \{0,1, 2, \ldots, \varsigma\}$ |
| $\boldsymbol{\mu_v^{r,s}}$ | Observed minimum travel time of EV type $v$ users travelling from origin $r$ to destination $s$ |
| $\boldsymbol{u_v^{r,s}}$ | Utility 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 $s$ |
| $\boldsymbol{\rho_{ij}^{r,s,v}}$ | Perceived cost for travelers, $= 0$ if link $(i, j)$ is on the feasible path; $> 0$ otherwise |
| $\boldsymbol{\eta_i^{r,s,v}}$ | 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 |

# LIST OF ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| **AFV** | Alternative-fuel Vehicle |
| **AV** | Autonomous Vehicle |
| **AEV** | Autonomous Electric Vehicle |
| **BEV** | Battery Electric Vehicle |
| **BPR** | Bureau of Public Roads |
| **CACC** | Cooperative Adaptive Cruise Control |
| **CAV** | Connected and Autonomous Vehicle |
| **CSP** | Constrained Shortest Path |
| **EV** | Electric Vehicle |
| **GA** | Genetic Algorithm |
| **GHG** | Greenhouse Gas |
| **HDV** | Human-driven Vehicle |
| **IDM** | Intelligent Driver Manual |
| **ICEV** | Internal Combustion Engine Vehicle |
| **MINLP** | Mixed-Integer Nonlinear Problem |
| **NCP** | Nonlinear Complementarity Problem |
| **NP-Hard** | Nondeterministic Polynomial-time Hard Problem |
| **NSGA-II** | Non-dominated Sorting Genetic Algorithm II |
| **PHEV** | Plugged in Hybrid Electric Vehicle |
| **UE** | User Equilibrium |
| **VOT** | Value of Time |

# NOMENCLATURE

| | |
|---|---|
| **AV-EV synergy** | Interaction and cooperation of AV and EV to produce a combined effect greater than the sum of their separate effects |
| **Tradeoff** | The exchange of something of value, especially as part of a compromise |
| **Transportation decision-maker** | Planner/policy maker in conjunction with private sector investor |
| **Lane type** | General-purpose lane and AV-exclusive lane |
| **General-purpose lane** | Regular lane for AV and HDV users |
| **AV-exclusive lane** | Dedicated lane for AV users |
| **EV driving range** | Estimated distance EV can drive at a given quantity of battery level |
| **EV charging facility method** | Static and dynamic charging |
| **Static charging** | Charging a parked EV |
| **Dynamic charging** | Charging an EV while moving |
| **Charging station** | Equipment that connects an EV with connector (cable) to a source of electricity to recharge it |
| **Wireless charging lane** | Equipment that recharges an EV without a connector (cable) while moving |
| **Charging rate** | Amount of range added to the EV battery per unit distance |
| **Charging station capacity** | Number of travelers that can use the EV charging station per unit of time |
| **Market penetration** | Measure of how much AV/HDV is being purchased by travelers |

# ABSTRACT

The emergence of Autonomous Vehicles (AVs) provides a valuable opportunity to reduce greenhouse gas emissions by improving traffic mobility. Due to AV-EV synergies, AVs will be likely introduced into the market when the Electric Vehicle (EV) market share is high. Hence, future AVs are expected to be electric, and it is anticipated that Autonomous Electric Vehicles (AEVs) will help address climate change and environmental pollution. This is the expectation particularly during the transition phase where mixed AV-HDV fleet will require lane management policies such as AV-exclusive lane. The possibility of installing wireless charging facility at AV-exclusive lanes is expected to motivate great patronage of AVs. This thesis proposes a planning framework for AEV charging. The framework is intended to help transportation decision-makers determine EV charging facility locations and capacities for the mixed fleet of AV and HDV. The bi-level nature of the framework captures the decision-making processes of the transportation agency decision-makers and travelers, thereby providing solid theoretical and practical foundations for the EV charging network design. At the upper level, the decision-makers seek to determine the locations and operating capacities of the EV charging facilities, in a manner that minimizes total travel time and construction costs subject to budgetary limitations. In addition, the transportation decision-makers provide AV-exclusive lanes to encourage AV users to reduce travel time, particularly at wireless-charging lanes, as well as other reasons, including safety. At the lower level, the travelers seek to minimize their travel time by selecting their preferred vehicle type (AV vs. HDV) and route. In measuring the users delay costs, the thesis considered network user equilibrium because the framework is designed for urban networks where travelers route choice affects their travel time. The bi-level model is solved using the Non-Dominated Sorting Genetic Algorithm (NSGA-II) algorithm. The results of the numerical experiments suggest that for a higher weight ratio of user cost dollar to agency cost dollar, the optimal deployment plan will include a greater number of wireless-charging facilities. Furthermore, the results suggest that, compared to the scenario where the transport decision-makers construct charging stations and where construct wireless-charging facilities, the scenario where the transport decision-makers construct both of them, the total costs decrease by 49% and 11%, respectively. It is shown that enabling wireless-charging facilities at both AV-exclusive and general-purpose lanes can reduce

total cost by 16% and 21% compared to plan where wireless-charging facilities are provided only at AV-exclusive and where are provided only at general-purpose lanes, respectively.

# 1. INTRODUCTION

## 1.1 Background and motivation

*(a) The problem of emissions*

The widespread use of fossil fuels (mainly, coal and petroleum) to meet energy requirements negatively impacts climate and the environment, such as global warming (Metz et al., 2007). Greenhouse gas (GHG) emissions resulting from fossil fuel use 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 (Council, 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 (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 (Ghosh, 2020; IEA, 2017; Miralinaghi & Peeta, 2019; Riba et al., 2016; K. Sinha & Labi, 2007).

*(b) The promise of AVs and AV-exclusive lanes*

The emergence of autonomous vehicles (AVs) provides a valuable opportunity to reduce transportation-related GHG emissions (Kopelias et al., 2020) because the connectivity technology of AVs allow platooning with reduced headways and this increases road capacity, improves traffic mobility (Ha et al., 2020) and reduces emissions. Tientrakool et al. (2011) showed that with full adoption of AVs, the road capacity could be tripled. On the other hand, 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.

*(c) The EV aspect of AEVs*

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). AEVs do not emit greenhouse gases, and therefore represent a promising solution to climate change and environmental pollution (Jochem et al., 2015; Liang et al., 2016). EVs are expected to significantly reduce GHG emissions compared to ICEVs (Xu et al., 2020). Specifically, it has been shown that EVs can reduce GHG emissions by 80% (Bauer et al., 2015). 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; Miralinaghi, Correia, et al., 2021). 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 & Waight, 2018). Also, Volvo announced in 2017 that its ICEV production line would end in 2019 as subsequent vehicles produced will all 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).

*(d) AEV charging and the alternatives*

Charging facility technologies are crucial to EV market penetration. Therefore, investigations regarding EV charging facilities planning and design are expected to help resolve the barriers that restrict the EV market share. A good balance between investment and use should be achieved in improving the EV charging facilities: if a limited number of 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 supply inefficiency. Appropriate and user-responsive types, locations, and capacities of charging infrastructure on the road network are essential for EV promotion.

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 process (Adler & Mirchandani, 2014). More importantly, it requires fast and easy operations, which is facilitated if the battery is standardized and easily replaceable. However, as the core EV technology is its battery pack, it seems unlikely that EV companies will achieve such standardization unless they cooperate (Liu & Wang, 2017).

Static charging is the most common charging method, and has three categories. In the first category, which is suitable for residential areas, the EV can be charged with AC 120 voltage outlet with 20-hr maximum charging time. In the second category, which is suitable for public parking, the EV can be charged with AC 280 voltage outlet with 7-hr maximum charging time. The third category uses 480 Volt AC/DC capacity, which charges the EV quickly (20 minutes). The third category allows EVs to be charged quickly, however, can hardly compete with the conventional ICEV that could usually be refilled in several minutes (Liu & Wang, 2017; Tabesh et al., 2019).

Wireless dynamic charging (referred to as wireless charging in this thesis), is another EV charging technology. EVs that use this technology do not require charging cable and connector. Wireless charging increases the driving range and reduces the charging time for EVs. The battery power can be 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). Due to the reduced battery weight, the EV propulsion power increases. Wireless charging offer EVs a potentially unlimited driving range as long as 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, a wireless charging facility is costly to construct, maintain, and operate (Gill et al., 2014) and has problems of electromagnetic compatibility, limited transfer of power, and lower efficiency due to the air-gap distance between the source and receiver (Grant Anthony Covic & Boys, 2013; Moon et al., 2014). In addition, wireless-charging lanes may end up as congested spots in the network as EVs may be attracted to them for recharging purposes. These lanes can reduce the capacity by 8%–17% because of the different driving manner in wireless-charging lanes (He et al., 2018). He et al. (2018) used car-following and lane-changing model to study the EV's driving behavior, and found that the wireless charging lanes would reduce the road capacity and increase the travel time. For conductive (charging with direct electrical contact between the power-source and the battery) wireless charging facilities the wireless charging lanes need to be continuous, however, inductive (charging the battery through an air gap) wireless charging facilities, which are considered as the wireless charging facility in this thesis, do not need continuous wireless charging lanes (Covic & Boys, 2013). Table 1-1 summarizes the merits and demerits of different EV-related infrastructure development options considered in this thesis.

Table 1-1. Merits and demerits of different EV-related infrastructure development options

| EV-related infrastructure development options | Merits | Demerits |
|---|---|---|
| Constructing new static charging stations | Addresses the current inadequacy of charging facilities<br>Helps reduce the range anxiety | Significant charging delay |
| Installation of wireless-charging facilities at general-purpose and/or AV-exclusive lanes | Addresses the current inadequacy of charging facilities<br>Helps reducing the range anxiety<br>Eliminates charging delay<br>Reduces the initial EV cost through battery downsizing | High cost of construction, maintenance, and operations<br>Absorbs high congestion on wireless-charging lanes |
| Conversion of general-purpose lanes (EAV, EHDV, CHDV) to AV-exclusive lanes (EAV) | Does not require ROW acquisition and construction<br>Separates AVs from HDVs and increases road capacity for AVs<br>Promotes AV ownership/use | Appropriates capacity available for HDVs |

*(e) Providing charging facility for AEV: business model*

To bring the wireless charging facility to market, a business model must be developed, which includes determining the costs, revenue source and how it will be obtained. A basic business model related to the deployment of wireless charging lanes: wireless charging lane as a classic road network, is studied by Bernecker et al. (2020). This model provides a conceptual basis for understanding of the ownership of wireless charging lane. The difference between wireless charging lane as a classic road network and traditional road network is that the road subsystem is simultaneously an energy system: it is electrified as well as the wireless charging equipment that need to be installed in the road network. According to this model, the transportation agency funds the installation of the wireless charging facility, owns the road, and is in charge of road operations, while private sector investors provide the electric infrastructure. The actual construction, maintenance, and operation of wireless charging facilities could also be provided by contracted service providers, which are private sector investors. Access to the road is generally free in this model, so any vehicle that is technically compatible could use it and simply pay energy bill which will most likely be calculated based on the amount of energy used. Table 1-2 summarizes the ownership/finance for stakeholders in the wireless charging facility business model.

Table 1-2. Ownership and finance for stakeholders

| Ownership/finance | Stakeholders | |
|---|---|---|
| | Public sector | Private sector |
| Ownership | Wireless charging lanes | Electric infrastructure |
| Costs | Installing wireless charging facilities | Construction, maintenance, and operation |
| Revenue | System concession | energy bill |

## 1.2 Problem Statement

Research is needed to promote EVs by providing models and results to help transport agencies understand the consequences of various EV infrastructure investment levels. This can be done by modeling and optimizing the types, locations, and capacities of the EV charging facilities while striking a balance between agency investment and travelers delay. It is needed to develop a framework for EV charging facility problem in the transition phase. During transition phase there are mixed fleet of AV and HDV. The EV charging facility location problem can be made subject to range constraints for both HDV and AV that are assumed to be EV. It is needed to develop an optimal plan that minimizes the agency cost, including the installation cost for both static and wireless-charging facilities, and user cost, including the total travel time.

## 1.3 Study Objectives

The main objective of the thesis 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 thesis uses a bi-level structure in which, at the upper level, the transportation agency decision-makers minimize construction cost and total system travel time cost, subject to the budgetary limitations, and 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 enables the agency to understand the impacts of the investment budget 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 behavior of travelers. This thesis considers intracity trips and does not consider transit (bus) wireless charging facilities.

## 1.4 Scope of the Study

This thesis considers two types of decision-makers: the transport agency's planner or policy maker (who decides the recommended (optimal) locations and capacities of static and wireless-charging facilities for mixed fleet of AV and HDV) and the private sector investor, who provide the funding and undertake the construction of the EV charging facilities. If the private sector investor is regarded as the only decision maker, society will be unable to afford because the private sector typically considers the charging facilities' profitability. Therefore, in this thesis, these two decision makers are regarded as primary decision makers and collectively referred as “the transport decision-makers”. In the context of this thesis, AV-exclusive lane deployment will not increase the overall number of lanes as it converts at least one general-purpose lane to AV-exclusive lane. Hence, it does not require right-of-way (ROW) acquisition and new construction.

## 1.5 Organization of the Thesis

This thesis has six chapters. Chapter 2 provides a literature review on EV charging facility planning, and the economic and operational impacts of EV infrastructure deployments. Chapter 0 presents the methodology, including the preliminary settings, assumptions, and the mathematical formulations. The solution algorithm used in this study, a metaheuristic, is explained in Chapter 4, and the numerical results and discussions are presented in Chapter 5. Chapter 6 concludes the study with a brief summary, conclusions and insights, recommendations for implementation, study limitations, and future research directions.

# 2. LITERATURE REVIEW

In this chapter, a review of existing literature was carried out in order to discuss the EV and AV synergy impacts, EV charging facility planning problem, and the economic and operational impacts of EV charging facility deployments. Also, past record on AV-exclusive lane impacts are discussed in this chapter.

## 2.1 Literature on EV and AV Synergies

There is a vast body of literature on the 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, only a few studies focused on Autonomous Electric Vehicles (AEVs) (Zhuge & Wang, 2021). Jochem et al. (2015) reviewed the literature on the environmental impacts of EVs, concluded that EVs represent a promising solution to climate change and environmental pollution challenges. Xu et al. (2020) demonstrated that EVs are expected to significantly reduce GHG emissions over a lifetime compared to ICEVs.

Autonomous Vehicles (AVs) are another disruptive innovation in the transport sector, are likely to be introduced into the vehicle market in the near future (Duarte & Ratti, 2018; González-González et al., 2019; Papa & Ferreira, 2018). A most recent study by Kopelias et al. (2020), demonstrated that AVs can help mitigate GHG emissions generated by improving traffic mobility. This is because AVs can travel without a driver and fully detect and respond to their surroundings with their sensor systems (Van Brummelen et al., 2018), and therefore ensure minimal headways (Ha, Chen, Dong, et al., 2020).

As an AV and EV synergy, Autonomous Electric Vehicles (AEVs) offer a promising solution to climate change and environmental pollution (Zhuge & Wang, 2021), as they embody the advantages of vehicle autonomy and electric propulsion. With their equipped sensors, AVs would be able to move at reduced headways and consequently, improves the traffic mobility, which can help to save energy (Fagnant & Kockelman, 2015). EVs are expected to significantly reduce GHG emissions over a lifetime compared to ICEVs (Xu et al., 2020), as they can achieve the same performance with less energy (Chau & Chan, 2007). Therefore, AEVs are generally expected to significantly reduce GHG emissions compared to HDVs which are mostly ICEVs.

## 2.2 Literature on EV Charging Facility Planning

AEV charging facility is an element that supplies electrical energy for charging autonomous EVs. It is important to address issues regarding the optimal locations, charging levels, and types of charging facility to help remove EV adoption barriers. Regarding the charging level of charging facilities, there are three levels of charging, levels 1 and 2 are referred to as slow charging and level 3 is referred to as fast charging. A few studies have studied slow charging (Frade et al., 2011; Jia et al., 2014). For example, Frade et al. (2011) introduced a model for slow-charging facility location to optimize demand coverage within an acceptable level of service. Various studies in recent years 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). For example, Navarro et al. (2019) modeled the design of an EV fast-charging in order to improve the profitability by decreasing the energy consumption.

In the context of 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). In particular, only a few studies considered wireless-charging facilities (Chen, 2016; He et al., 2013; Liu & Wang, 2017; Riemann et al., 2015). For example, He et al. (2013) presented a mathematical model to determine the optimum prices of electricity for wireless-charging lanes to maximize social welfare. Using a similar approach, Riemann et al. (2015) investigated the optimal location of wireless-charging facilities to capture the optimum flow of traffic on the network while considering the users' route choice behavior. Chen et al. (2016) developed a wireless-charging lane deployment model with user equilibrium to optimize the location of wireless-charging lanes within a given budget. More recently, Liu et al. (2017) proposed a model for deciding the locations of static and dynamic charging facilities to maximize social welfare and minimizing total system travel time and the penalty for "failed" trips affected by insufficient remaining battery charge. Although they considered multiple types of charging facilities and EVs, Liu et al. (2017) assumed that vehicles can use only one not both of the charging facilities at a time.

## 2.3 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 the facility location in the context of EV charging facilities. Based on the route choice behavior of the travelers (EV users), these studies can be classified into two groups.

The first group addresses the location of EV charging facilities without consideration of 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, considered intercity trips, and did not consider the impact of congestion on the facility location problem. Yang et al. (2017) also considered long-distance travel routes. In their study, battery-swapping station locations were modeled to maximize the total benefit of battery leasing. Due to the long distances, they assumed travelers' travel time as constant, and the impact of charging facility location on congestion was not considered. Using a similar approach, Wang et al. (2016) modeled the charging facility location problem for charging stations and developed the EV charging station construction schedules by assuming a constant path for each EV. All these studies broke new ground in the context of the EV charging facility location problem. However, assuming a constant path for each EV in the network can be considered rather too restrictive, and needs to be addressed.

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

## 2.4 Literature on Impacts of AV-Exclusive Lanes

AVs are expected to have a beneficial effect on the transportation 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 could increase the road capacity by up to 273%. In addition, with regard to 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 simulations. Van Arem et al. (2006) simulated AVs to study the impact of the AV-exclusive lanes and found that the average road 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 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 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 be important. In various AV growth scenarios in the Netherlands, Correia et al. (2019) reported a potential VOT decrease of between 1% and 31% for AV users (level 3 and higher).

## 2.5 Literature on Tradeoffs

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

## 2.6 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 business model for wireless charging facility seems most likely to be in form of public-private partnership. According to Bateman et al. (2018), the capital cost and investment risk are too high for most private sector investors to be sole investors. Government funding is required because the government is more likely to accept longer payback times than private investors, and is more likely to invest in technologies that result in emissions savings. 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, according to Bernecker et al. (2020), access to the road is considered free, and any vehicle that is compatible 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 infrastructure is provided by private sector investors. In the second model, access to the road is only available to customers who pay for access. In this case, road access is limited, as in the case of the toll ways.

## 2.7 Summary

This chapter reviewed the literature on EV and AV synergies, the EV charging facility location problem and studies that considered the impact of AV-exclusive lanes. In the literature, several studies have studied the EV charging facility problem. However, focusing on only locating one type of EV charging facility for HDVs in the network can be considered rather too restrictive. Clearly, there is a need for a comprehensive decision framework for EV charging facility problem that considers locations, capacities, and multiple types of the EV charging facilities, for mixed fleet of AVs and HDVs. This thesis offers two contributions. Most notably, it develops a bi-level multi-objective framework where the transportation decision-makers seek to optimally design the EV charging facilities for mixed-fleet of AVs and HDVs. Further, this thesis determines the impacts of installing wireless-charging facilities on general-purpose and AV-exclusive lanes on route choice and vehicle type choice behavior of travelers. Table 2-1 summarizes the related studies, and highlights the contrast between past studies and this thesis.

Table 2-1. Review of literature: a comparison of past studies

| Reference | Vehicle type | Charging mode | Charging speed | Study objective | User equilibrium |
|---|---|---|---|---|---|
| Ghamami et al. (2020) | EV (HDV) | Static | Fast charging | Minimize infrastructure cost and users' detour, waiting, and charging delay. | Yes |
| Hayato et al. (2017) | EV (HDV) | Dynamic | N/A | Minimize construction cost. | Yes |
| He et al. (2018) | EV (HDV) | Static | Fast charging | Maximize path flows that patronize the charging stations. | Yes |
| Lee et al. (2017) | EV (HDV) | Static | Fast charging | Maximize the total sum of flows covered while minimizing the number of recharging stations. | Yes |
| Liu and Wang (2017) | EV (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) | EV (HDV) | Static | Fast charging | Minimize total system travel time and energy use. | Yes |
| Chen et al. (2016) | EV (HDV) | Dynamic | N/A | Minimize total system travel time. | Yes |
| Zhu et al. (2016) | PHEV (HDV) | Static | Fast charging | Minimize the total charging station construction costs. Attain a desired traveler convenience. | Yes |
| Chen et al. (2013) | EV (HDV) | Static | Fast charging | Minimize EV users' station access cost with penalizing unmet demand. | Yes |
| Yang et al. (2017) | EV (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) | PHEV/EV (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) | EV (HDV) | Static | Fast charging | Minimize total cost of new charging stations and relocations during planning horizon. | No |
| Wang et al. (2016) | EV (HDV) | Static | Fast charging | Minimize total operational and construction costs. | No |
| Arslan and Karasan (2016) | PHEV/EV (HDV) | Static | Fast charging | Minimize total traveled distance. | No |
| Cavadas et al. (2015) | EV (HDV) | Static | Fast charging | Maximize EV charging demand satisfaction. | No |
| Huang et al. (2015) | AFV (HDV) | Static | Fast charging | Minimize total construction cost. | No |
| Hosseini and Mirhassani (2015) | AFV (HDV) | Static and dynamic | Fast charging | Maximize total covered demand. | No |
| de Almeida Correia and Santos (2014) | ICEV/EV (HDV) | Static | Slow charging | Maximize profit of rental car company. | No |
| Frade et al. (2011) | EV (HDV) | Static | Slow charging | Maximize total covered demand. | No |
| Wang and Wang (2010) | AFV (HDV) | Static | Slow charging | Minimize total construction cost and maximize total covered demand. | No |
| **This thesis** | **EV (AV/HDV)** | **Static and dynamic** | **Fast charging** | **Minimize total system travel time and construction cost of EV charging infrastructure.** | **Yes** |

# 3. METHODOLOGY

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

## 3.1 Introduction

The EV charging facility location problem is formulated as a bi-level program consisting of upper-level and lower-level models (Figure 3-1). 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 control decisions for travelers are to select the 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 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 depend 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.

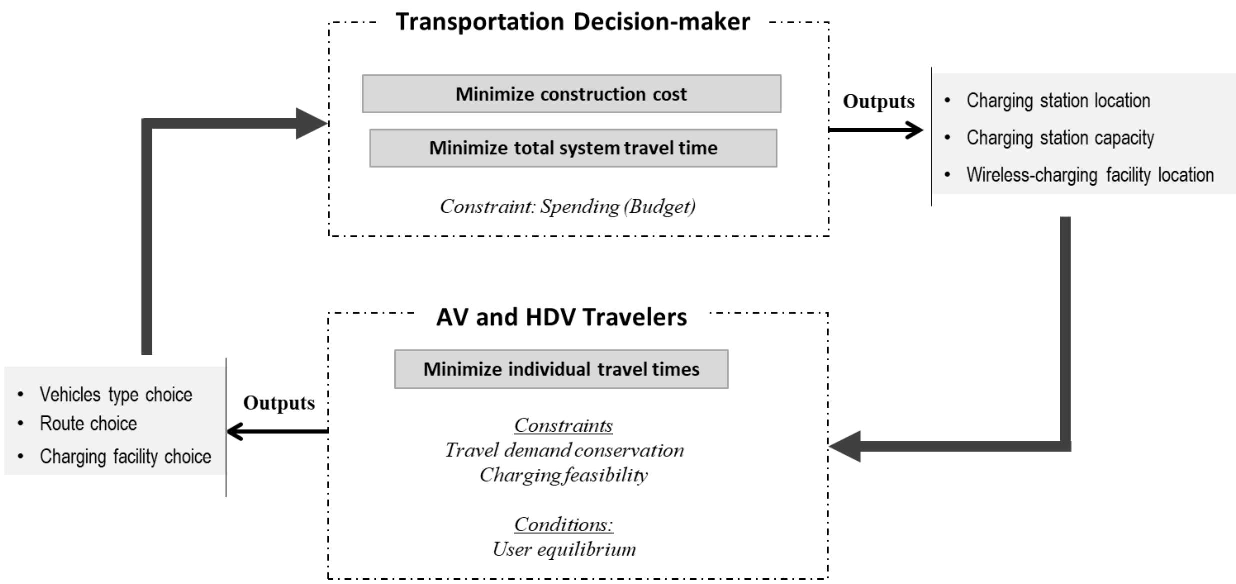



Figure 3-1. Bi-level nature of the framework

### 3.2 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 sets $A'$ and $\bar{A}$ are a subset of $A$.

In addition, $t_{ij}$ and $x_{ij}$ represent the travel time and the link flow of link $(i, j)$, respectively. The travel time of link $(i, j)$ follows the Bureau of Public Roads (BPR) function, which can be expressed as:

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

where $t_{0,ij}$ and $\chi_{ij}$ denote the free-flow travel time and capacity of the link $(i, j)$, respectively.

This thesis 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. 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 3-2. Figure 3-2(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 3-2(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.

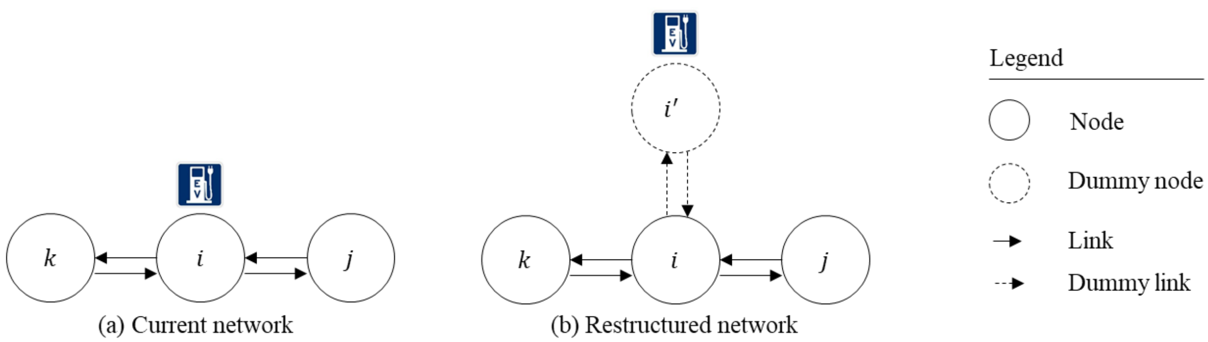



Figure 3-2. Transformation of the traffic network at nodes with charging stations

### 3.3 Assumptions

A number of assumptions were made in this study. First, the mixed fleet of AV and HDV considered to be electric. This is an important assumption because in the literature it is suggested 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 shared AVs' recharging needs are often different from private AVs. Third, it is assumed that the transportation decision-maker takes into account varying levels of charging station capacity. $y_k$ is an integer variable representing the capacity level of the charging station on candidate node $k$. $y_k > 0$ indicates the electric charging station of node $k$ operates at level $y_k$ and $=\ 0$ indicates the 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 $\gamma_k$ 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 economics, as follows:

$$\mathrm{F}(y_k) = \iota_1 + \iota_0 \cdot y_k \cdot \gamma_k^1 \qquad \forall k \in K_1 \qquad (2)$$

where $\iota_0$ and $\iota_1$ represent the variable 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:

$$\mathrm{F}'(z_{k'}) = \pi_1 + \pi_0 \cdot z_{k'} \cdot \chi_{k'} \qquad \forall k' \in K' \qquad (3)$$

where $\pi_0$ and $\pi_1$ 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 3-3. Figure 3-3 (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 3-3 (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.

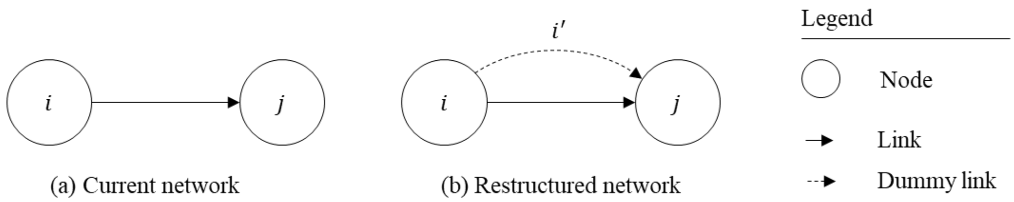



Figure 3-3. Transformation of the traffic network at links with AV-exclusive lane

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 thesis. 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 function of travel distance.

## 3.4 Upper-Level Model

At the upper level, as stated earlier, by offering EV charging stations at nodes and wireless-charging facilities at optimum link locations and operating levels, the transportation decision-makers seek to minimize the total travel time costs ($\phi_1$) and construction costs ($\phi_2$). Relative weights are assigned to the agency cost (construction cost) and the user cost (travel time cost). Then the overall cost of upper-level objective ($Z^U$) can be calculated as the weighted sum of these costs. The upper-level model can be formulated as follows (Equations (4)-(8)):

$$Z^U = \min[(1-\xi)\phi_1 + \xi \cdot \phi_2] \tag{4}$$

$$0 \le \xi \le 1 \tag{a}$$

$$\phi_1 = \sum_{(i,j)\in A} \theta^v t_{ij}\left(x_{ij}^v\right) x_{ij}^v \tag{b}$$

$$\phi_2 = \sum_{k \in K} \mathrm{F}(y_k) + \sum_{k' \in K'} \mathrm{F}'(z_{k'}) \quad \text{(c)}$$

$$\sum_{k \in K} \mathrm{F}(y_k) + \sum_{k' \in K'} \mathrm{F}'(z_{k'}) \leq B \quad (5)$$

$$x \in x^{\text{lower level}}, t \ \in t^{\text{lower level}} \quad (6)$$

$$y_k \ \in \ \{0,1,2,\dots,\varsigma\} \qquad \forall k \in K \quad (7)$$

$$z_{k'} \ \in \ \{0,1\} \qquad \forall k' \in K' \quad (8)$$

where $\xi$ denotes the weight of construction cost relative to total travel time cost, $\varsigma$ is the maximum capacity level of charging stations, and $B$ is the construction budget. The objective function 4 ((a)-(c)) minimizes total system travel time cost and cost of constructing charging facilities. Constraint (5) ensures that the budget constraint for constructing the charging facilities is satisfied. Constraint (6) states that the link flows and travel times are derived from the lower-level model. Finally, constraints (7) and (8) specify the integer and binary domains of the upper-level decision variables, respectively.

### 3.5 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 transport agency decision-maker in 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 purchasing price of the vehicles. This model is widely used in the literature to capture travelers' vehicle type choices (Liu & Wang, 2017). 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:

$$u_v^{r,s} = \frac{\beta_0 C_v}{YW} + \beta_1 \cdot \mu_v^{r,s} \qquad \forall (r,s) \in OD, v \in V \qquad (9)$$

$$P_v^{r,s} = \frac{\exp(u_v^{r,s})}{\sum_{v \in V} \exp(u_v^{r,s})} \qquad \forall (r,s) \in OD, v \in V \qquad (10)$$

$$d_v^{r,s} = d^{r,s} P_v^{r,s} \qquad \forall (r,s) \in OD, v \in V \qquad (11)$$

where $\beta_0$ and $\beta_1$ denote the weights for vehicle purchasing price and travel time cost, respectively, $Y$ and $C_v$ represent the average life expectancy and purchasing price of the vehicles. $W$ represents the users' average wage rate ($/hr). Equation (9) calculates the utility of users traveling from origin $r$ to destination $s$ choosing EV type $v$. Then, Equation (10) calculates the probability of choosing EV type $v$ of users traveling from origin $r$ to destination $s$. Finally, Equation (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 thesis 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:

$$b_j^{r,s,v} \leq b_i^{r,s,v} - L_{ij} + r_{ij} - M \cdot \left(1 - e_{ij}^{r,s,v}\right) \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad (12)$$

$$b_i^{r,s,v} \leq \bar{R} \qquad \forall i \in N, \forall (r,s) \in OD, v \in V \qquad (13)$$

$$b_r^{r,s,v} = \bar{\bar{R}} \qquad \forall (r,s) \in OD, v \in V \qquad (14)$$

$$r_{ij} = R_{ij} \cdot \left(z_{ij} + y_{ij}\right) \qquad \forall (i,j) \in A \qquad (15)$$

$$b_i^{r,s,v} \geq 0 \qquad \forall i \in N, \forall(r,s) \in OD, v \in V \tag{16}$$

$$e_{ij}^{r,s,v} \in \{0,1\} \qquad \forall(i,j) \in A, \forall(r,s) \in OD, v \in V \tag{17}$$

$$z \in z^{\text{upper level}}, y \in y^{\text{upper level}} \tag{18}$$

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 (12) derives the residual range of EVs of type $v$ at node $i$ traveling from origin $r$ to the destination $s$. Constraints (13) ensures that the residual range of EVs does not exceed the maximum range of the vehicle. Constraint (14) ensures that the driving range of EVs is equal to the initial (pre-trip) driving range of vehicle at the trip origin. Constraint (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 (16) guarantees the non-negativity of the driving range, and constraint (17) specifies the binary domain of the $e_{ij}^{r,s,v}$. Finally, constraint (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 transport agency decision-maker in the upper level, a multi-class traffic assignment is developed. Suppose that road users always choose the route with minimum travel costs to complete their trips. Therefore, we can define the user equilibrium according to the first principle of Wardrop (1952). In equilibrium, for travelers traveling from origin $r$ to destination $s$ on the same type of vehicle, the travel cost on all the paths used is equal to the minimum travel cost. The multi-class traffic assignment model can be formulated as follows:

$$\min Z^L = \sum_{(i,j)\in A} \int_0^{x_{ij}} t_{ij}(\omega) d\omega \tag{19}$$

$$\sum_{v\in V} \sum_{(r,s)\in OD} x_{ij}^{r,s,v} = x_{ij} \qquad \forall(i,j) \in A, v \in V \tag{20}$$

$$\sum_{j:(j,i)\in A} x_{ji}^{r,s,v} - \sum_{j:(i,j)\in A} x_{ij}^{r,s,v} = q_i^{r,s,v} \qquad \forall(r,s) \in OD, v \in V, \forall i \in N \tag{21}$$

$$x_{ij}^{r,s,v} \leq M \cdot e_{ij}^{r,s,v} \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad (22)$$

$$x_{ij}^{r,s,v} \geq 0 \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad (23)$$

$$\mu_v^{r,s} = \sum_{(i,j) \in A} e_{ij}^{r,s,v} \cdot t_{ij} \qquad \forall (r,s) \in OD, v \in V \qquad (24)$$

$$e_{ij}^{r,s,2} = 0 \qquad \forall (i,j) \in A', \forall (r,s) \in OD \qquad (25)$$

where $q_i^{r,s,v}$ is defined as follows:

$$q_i^{r,s,v} = \begin{cases} -d_v^{r,s} & \text{if } i \text{ is the origin of OD pair} \\ 0 & \text{if } i \text{ is an intermediate node} \\ d_v^{r,s} & \text{if } i \text{ is the destination of OD pair} \end{cases} \qquad \forall i \in N, \forall (r,s) \in OD, v \in V \qquad (26)$$

The objective function (19) and constraints (20), (21), (23), and (26) represent the conventional traffic assignment function. Constraint (22) states that users can only use their corresponding feasible subnetworks. Constraint (24) calculates the travel time of EVs of type $v$ traveling from origin $r$ to destination $s$. Constraint (25) ensures that the HDV travelers do not use AV-exclusive link. Finally, Constraint (23) guarantees the non-negativity of the link flows.

To develop a tractable bi-level formulation, it is necessary to formulate the first-order conditions of the model (19)-(23) to eliminate objective function (19). Let $\eta_i^{r,s,v}$ denote a Lagrangian multiplier of travel demand conservation constraints (21) which is the minimum cost of EV type $v$ to travel to node $i$ traveling from origin $r$ to destination $s$. Let $\rho_{ij}^{r,s,v}$ denote the Lagrangian multiplier of the constraints (22). The first-order conditions of conventional traffic assignment model can be written as follows:

$$x_{ij}^{r,s,v} \cdot \left(t_{ij}(x_{ij}) + \rho_{ij}^{r,s,v} + \eta_i^{r,s,v} - \eta_j^{r,s,v}\right) = 0 \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad (27)$$

$$t_{ij}(x_{ij}) + \rho_{ij}^{r,s,v} + \eta_i^{r,s,v} - \eta_j^{r,s,v} \geq 0 \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad (28)$$

$$x_{ij}^{r,s,v} \leq M \cdot e_{ij}^{r,s,v} \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad (29)$$

$$\rho_{ij}^{r,s,v} \leq M \cdot \left(1 - e_{ij}^{r,s,v}\right) \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \qquad (30)$$

$$\eta_r^{r,s,v} = 0 \qquad \forall (i,j) \in A, \forall (r,s) \in OD, v \in V \tag{31}$$

$$e_{ij}^{r,s,2} = 0 \qquad \forall (i,j) \in A' \cup A'', \forall (r,s) \in OD \tag{32}$$

$$\sum_{j:(j,i)\in A} x_{ji}^{r,s,v} - \sum_{j:(i,j)\in A} x_{ij}^{r,s,v} = q_i^{r,s,v} \qquad \forall (r,s) \in OD, v \in V, \forall i \in N \tag{33}$$

$$\rho_{ij}^{r,s,v}, x_{ij}^{r,s,v}, \eta_i^{r,s,v} \geq 0 \qquad \forall (i,j), \forall w, \forall t, \forall m \tag{34}$$

Constraints (27) and (28) are the user equilibrium conditions which ensure that if travelers of each OD pair use link $(i,j)$, it belongs to the feasible path. Otherwise, there is an extra perceived cost for travelers which discourages their patronage of this link. Constraints (30) state that if a link $(i,j)$ does not belong to the feasible subnetwork, then there is an extra perceived cost for using the link $(i,j)$.

## 3.6 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 thesis, there are many types of tradeoff, 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, based on the logit model presented in Section 3.5, 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 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 require to deviate from their optimal route (including AV-exclusive lanes) to recharge.

### 3.7 Summary of the Chapter

This chapter presented the methodology for the thesis. First, Section 3.1 introduced the bi-level framework of the problem, and Section 3.2 presented the preliminaries. The assumptions made in this study were discussed in detail in Section 3.3. The upper-level and lower-level models were represented in Sections 3.4 and 3.5, respectively. The transportation decision-makers' decisions are modeled using the upper-level model, and the travelers' route choice and vehicle type choice are modeled using the lower-level models.

# 4. 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. The following describes in detail solution approach for each level.

## 4.1 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 is known to be NP-hard (Bazaraa et al., 2013). In this thesis, 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; Miralinaghi, Davatgari, et al., 2021). At the lower level, for the travelers 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.

## 4.2 Upper-Level Solution Approach

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 4-2.

*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 4-1. Each chromosome is a set of $n$ candidate links for wireless charging and $m$ candidate nodes for charging stations. Each cell of represented chromosome in Figure 4-1, 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.

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

Figure 4-1. Representation of each chromosome

*Step 2:* The objective value of the upper-level model (4 (a), 4 (b)) is determined for each chromosome. To do so, the construction cost 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 thesis. 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.

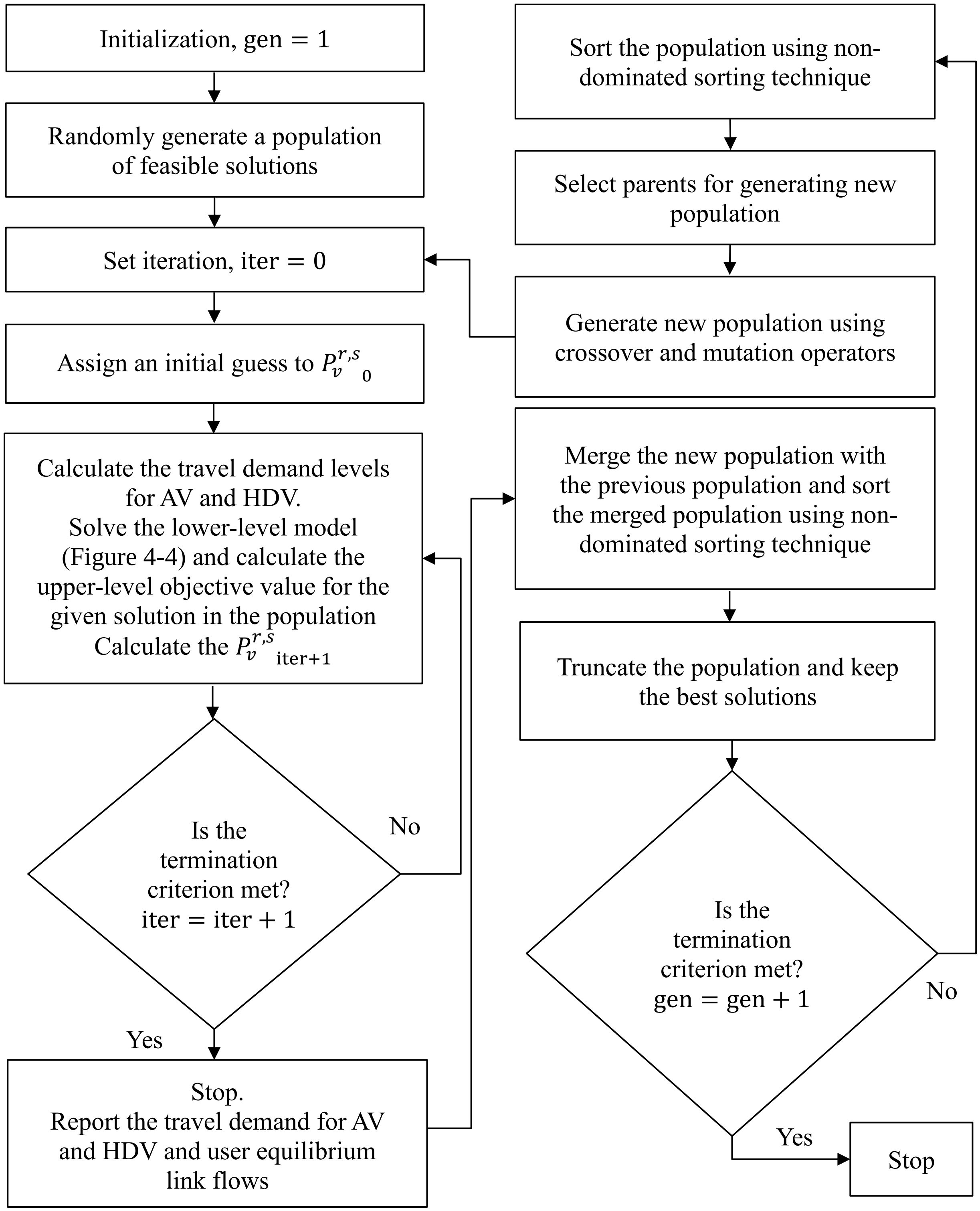



Figure 4-2. Algorithm flowchart

## 4.3 Lower-Level Solution Approach

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 a traditional solution methods, the Franke-Wolfe algorithm (1956), is used to solve the user equilibrium model, which is a well-known algorithm for solving traffic assignment problems. In the sections that follow, the solution approach for vehicle type and route choices of travelers is discussed in detail.

### 4.3.1 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 Section 4.3, the UE solution method is explained. This section seeks to predict the travel demand for AV and HDV users, taking into account 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 $\mathrm{x} = \mathrm{f(x)}$ and then to use the iterative scheme ($\mathrm{x}_{\mathrm{iter+1}} = \mathrm{f}(\mathrm{x}_{\mathrm{iter}})$) with an initialization of $\mathrm{x}_0$. Repeat this process until the stopping condition is satisfied. The AV and HDV user demands 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 (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 (9), the probability of choosing AV/HDV (${P_v^{r,s}}_{\mathrm{iter+1}}$) can be derived from Equation (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 ($\epsilon$), 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.

### 4.3.2 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 4.3.1. 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 is needed 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 the constrained shortest path algorithm proposed by Bahrami et al. (2017) is first discussed in detail, and then, the Frank-Wolfe algorithm is described in a step-by-step manner.

***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. Despite 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 $v$. Since Bellman's algorithm solves the shortest path problem based only on travel time, 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. In order 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 the modification they made ensures that the shortest path generated is feasible and optimal.

As shown in the algorithm pseudocode (Figure 4-3), 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 4-3. Constrained shortest path (CSP) algorithm pseudocode

### ***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 4-4 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 $\mathrm{iter} = 0$ 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 origin-destination pair to the generated shortest path.

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

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

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

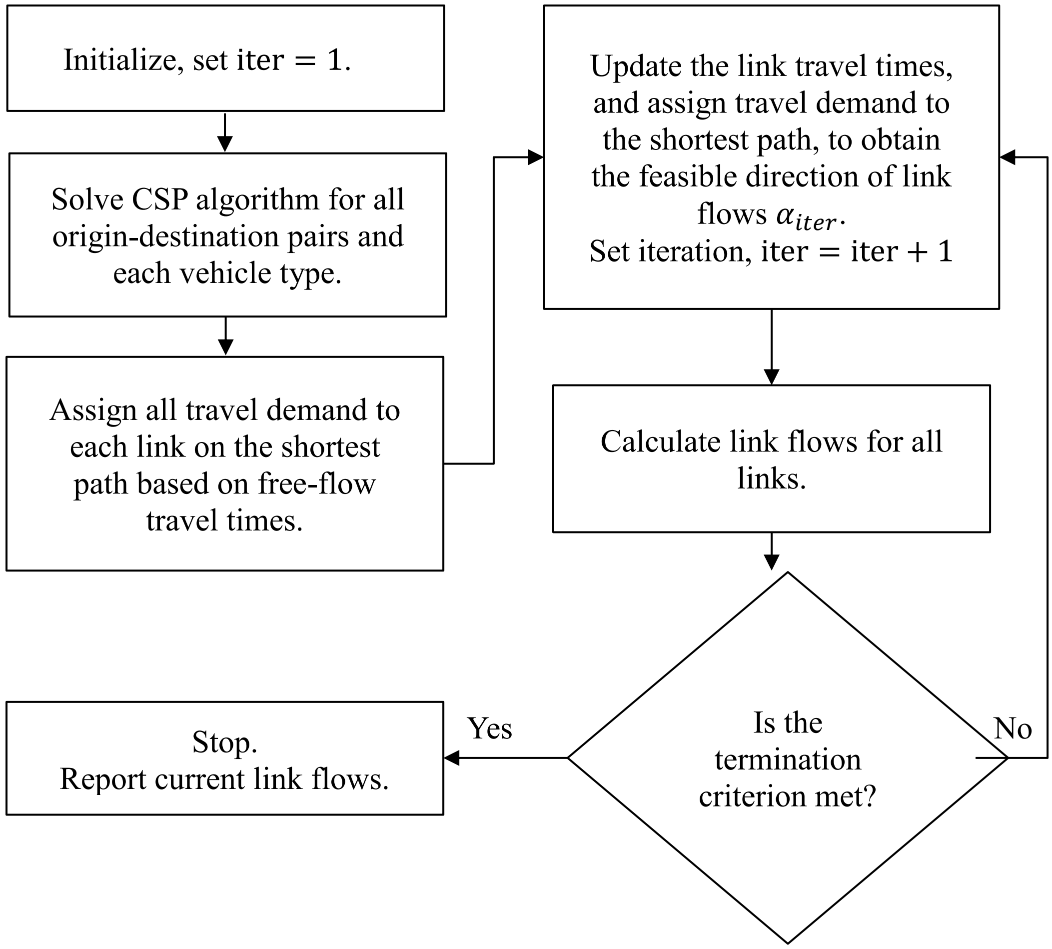



Figure 4-4. Lower-level solution flowchart

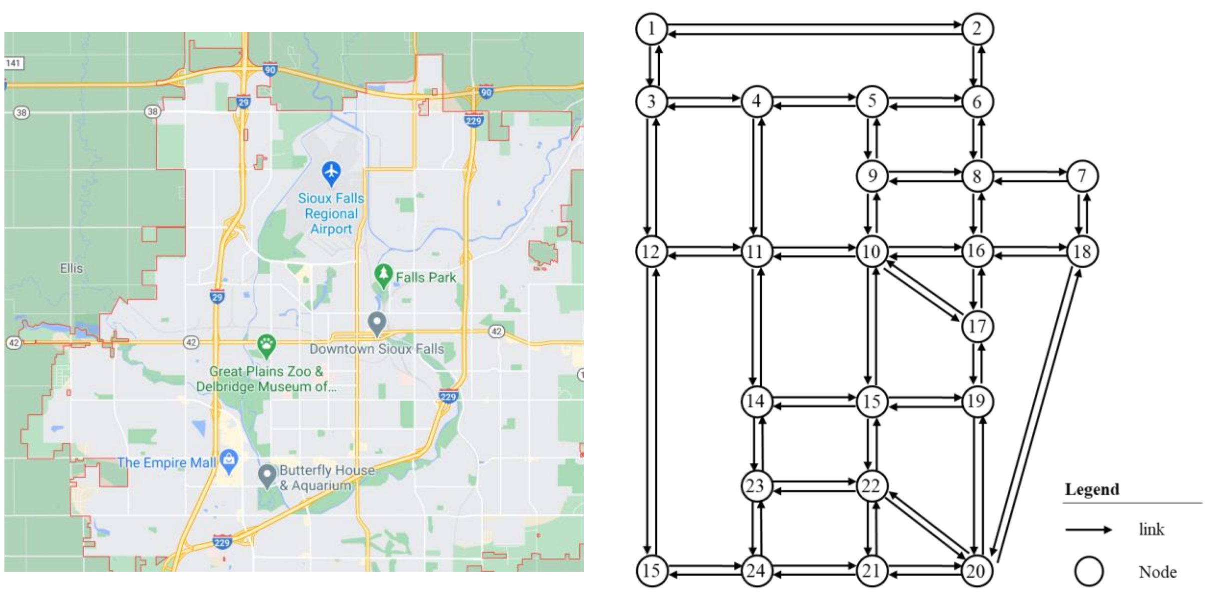
## 4.4 Summary of the Chapter

This chapter discussed 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 derived solving the logit model using the solution algorithm presented in Section 4.3.1. Then the user equilibrium link flows were calculated using Frank-Wolfe algorithm presented in Section 4.3.2. 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 be left for the next iteration. This iterative scheme was repeated until the stopping criterion had been met.

# 5. NUMERICAL EXPERIMENTS

## 5.1 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 5-1) has 24 nodes and 76 links. The network characteristics and travel demands 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 purchasing price.




(a) North Dakota

(b) Sioux Fall road network

Figure 5-1. Sioux-Falls road network

## 5.2 Computational Setting

As shown in Figure 5-2, the Sioux Falls road network has been associated with fourteen (14) potential AV-exclusive lanes (red arrows in Figure 5-2) by Chen et al. (2016). We have considered similar locations for the AV-exclusive lanes as Chen et al. (2019) proposed. According to Tientrakool et al. (2011), the capacity of AV-exclusive lanes are assumed to be 43% greater than that of general-purpose lanes at the same link. This is because capability of AVs enables them to move at reduced headways and consequently, increases the road capacity. In Figure 5-2, 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.

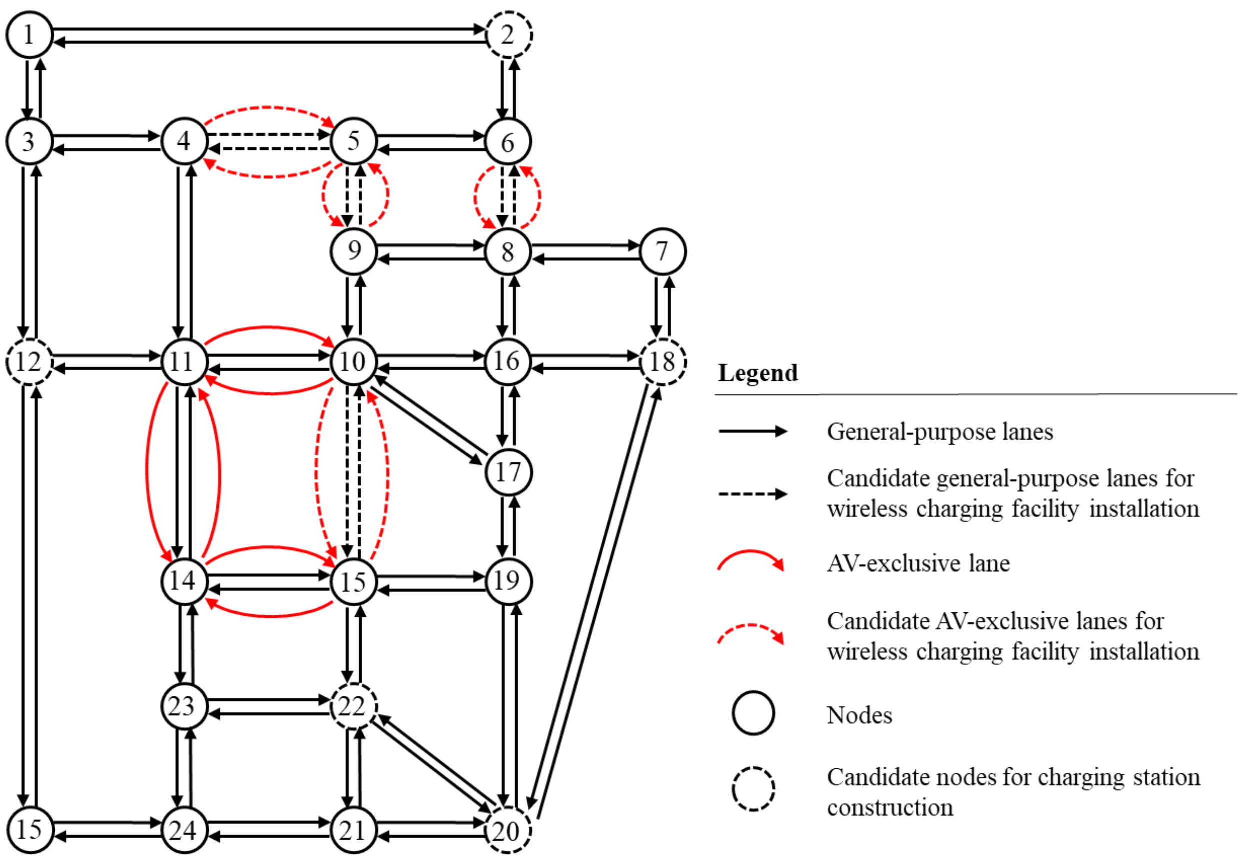



Figure 5-2. Candidate nodes and links for EV charging facility

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 constructing cost can be calculated using Equation (2). In other words, the construction cost of levels 1 and 2 charging stations with capacities of 300 and 600 veh/hr are equal to $1 and $1.8 million, respectively (Table 5-1).

Table 5-1. Cost of constructing charging stations at candidate nodes

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

According to Fuller et al. (2016), the average installation, and the annual operations, and maintenance costs of a wireless-charging facility is $4 million per mile per lane. Based on this average cost of installing wireless-charging facility on the candidate links of the case study network can be calculated using equation (3), and results are provided in Table 5-2.

Table 5-2. 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 |

In the base analysis, based on the EV charging facility construction costs, the construction 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 5.6. 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), compare 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 purchasing price of the vehicle in the utility function (Equation (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 purchasing 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.

## 5.3 Base Analysis

The Pareto frontier obtained using the NSGA-II algorithm for the case study is illustrated in Figure 5-3. 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 5-4 (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 5-4 (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 5-4 (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 5-4 (d). Table 5-3 summarizes obtained PO solutions for the case study.

Table 5-3. PO solutions for EV charging facility locations, costs

| Pareto Optimal Solution | Charging station locations and capacities | Wirelesscharging 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 |

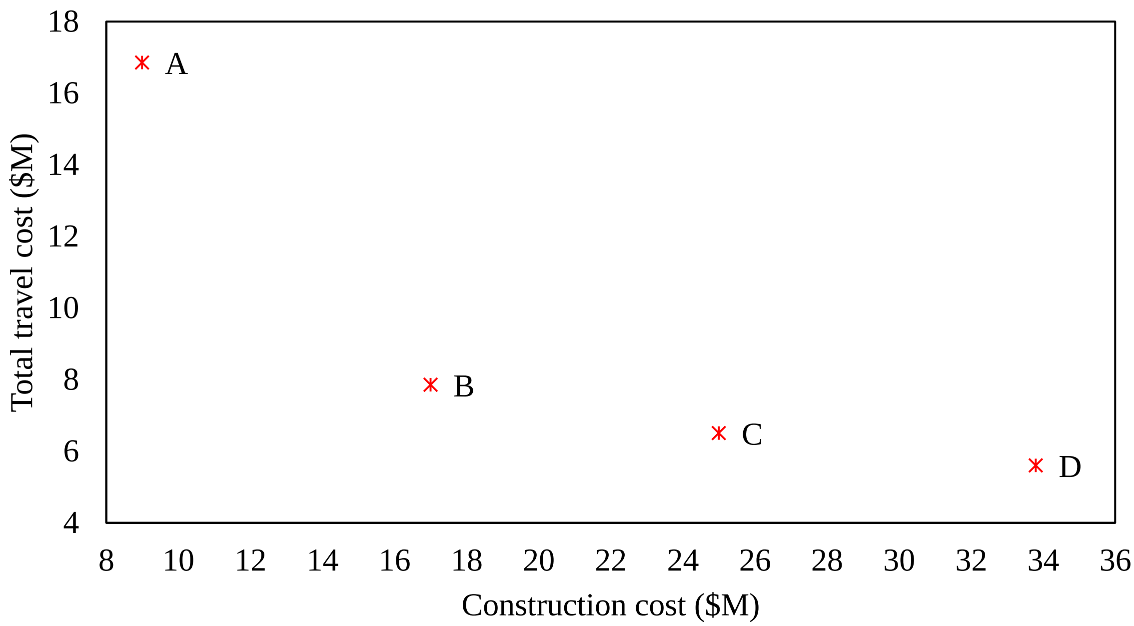
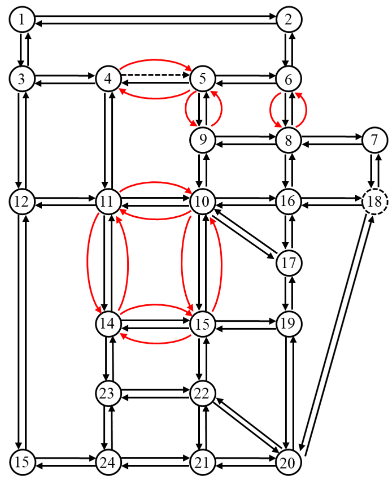
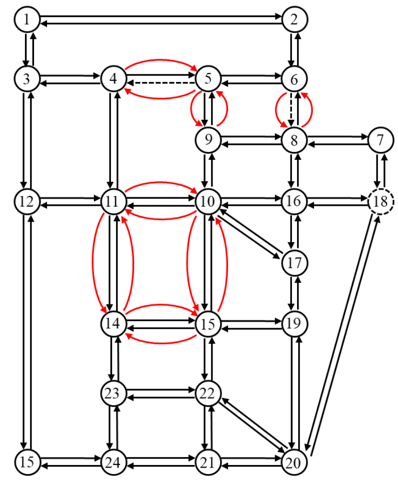


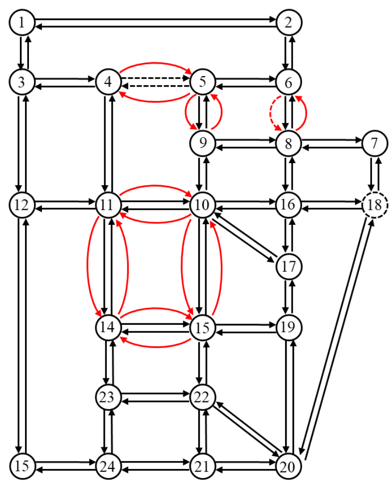

Figure 5-3. PO solutions for the case study



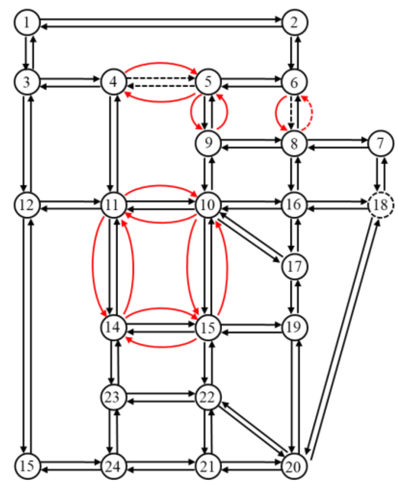
(a) Pareto optimal solution "A"



(b) Pareto optimal solution "B"



(c) Pareto optimal solution "C"



(d) Pareto optimal solution "D"

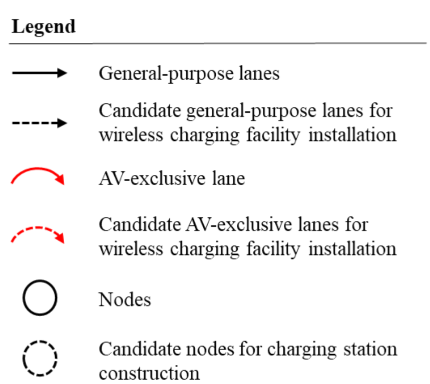



Figure 5-4. PO solutions for EV charging facility location, the Sioux Falls road network

Figure 5-5 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.

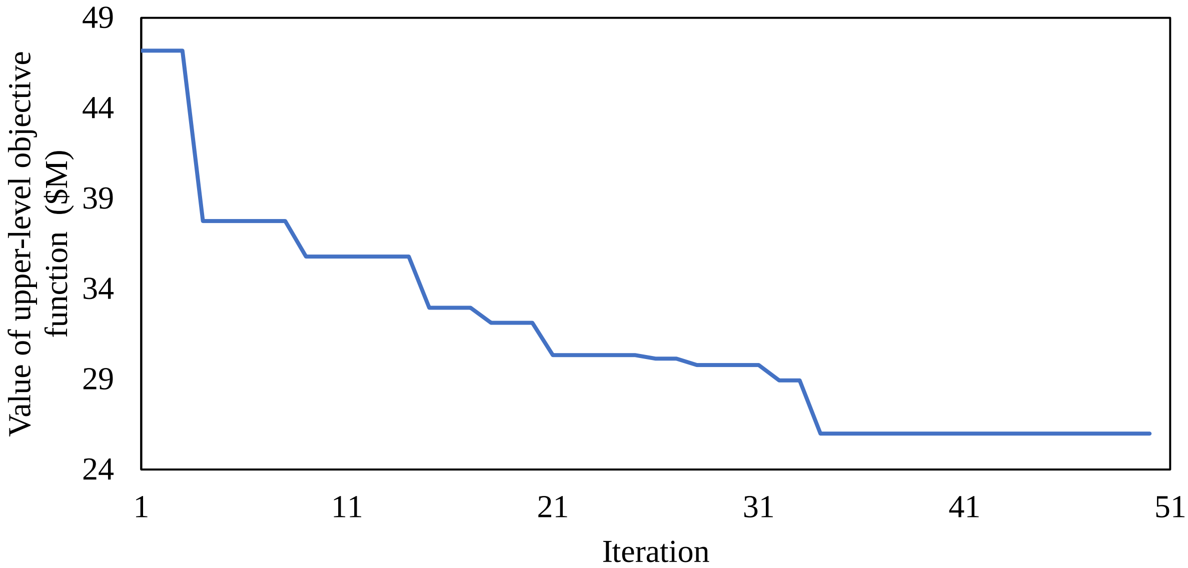



Figure 5-5. Convergence of the upper-level objective function over the iterations.

## 5.4 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 thesis, 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 that the transportation decision-makers can reduce total travel time costs by increasing the EV charging facility investment. Hence, if the transportation agency considers the costs of travelers to be of significant importance, 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, model decides to install more wireless-charging facilities rather than charging stations. This is because wireless-charging facilities have lower charging delay compared to charging stations.

### 5.5 Sensitivity Analysis on the Impact of Weights on the Optimal Solution

In making decisions based on multiple criteria, the transportation agency 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? 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 thesis, 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 agency (Labi, 2014). As such, it is often useful to assess the sensitivity of the optimal solution to changes in the weights. 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:

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

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

where $\xi$ denotes the weight of construction cost relative to the user cost. Figure 5-6 illustrates the impacts of changes in agency-user cost weight ratio ($\xi$) 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 significant importance; the strategy of PO solution "D" will be chosen. With increasing the importance of construction 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, $\xi = 0.65$.

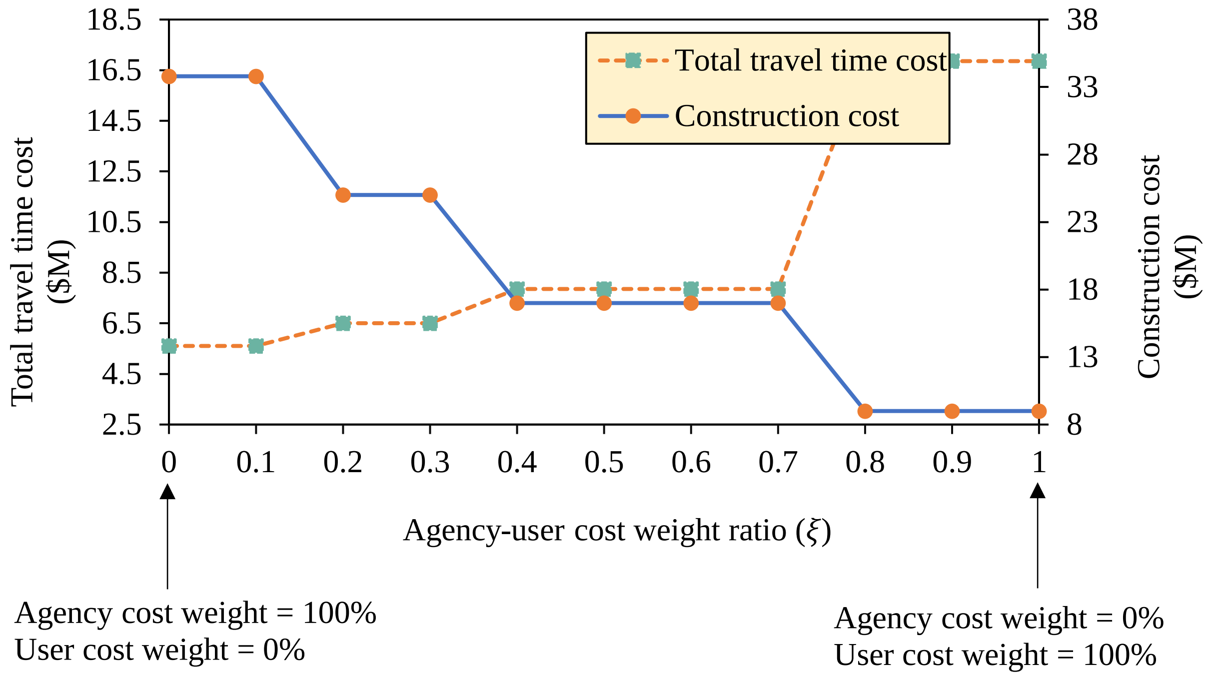



Figure 5-6. Impact of weights on the optimal costs

## 5.6 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 5-4 presents the three scenarios (levels) of the construction budget and Table 5-5 presents the results.

Table 5-4. Different construction budget levels (in million dollars)

| Budget scenario | Construction budget |
|---|---|
| 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 recharging, and therefore does not involve construction of any charging facility 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. Figure 5-7 presents the impacts of different factors on travel time and AV/HDV market penetration. 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. And with a reduction in travel time costs, AV market penetration decreases due to higher purchasing price compared to HDV. In the rest of this chapter, the results of each scenario are compared with those of scenario 0.

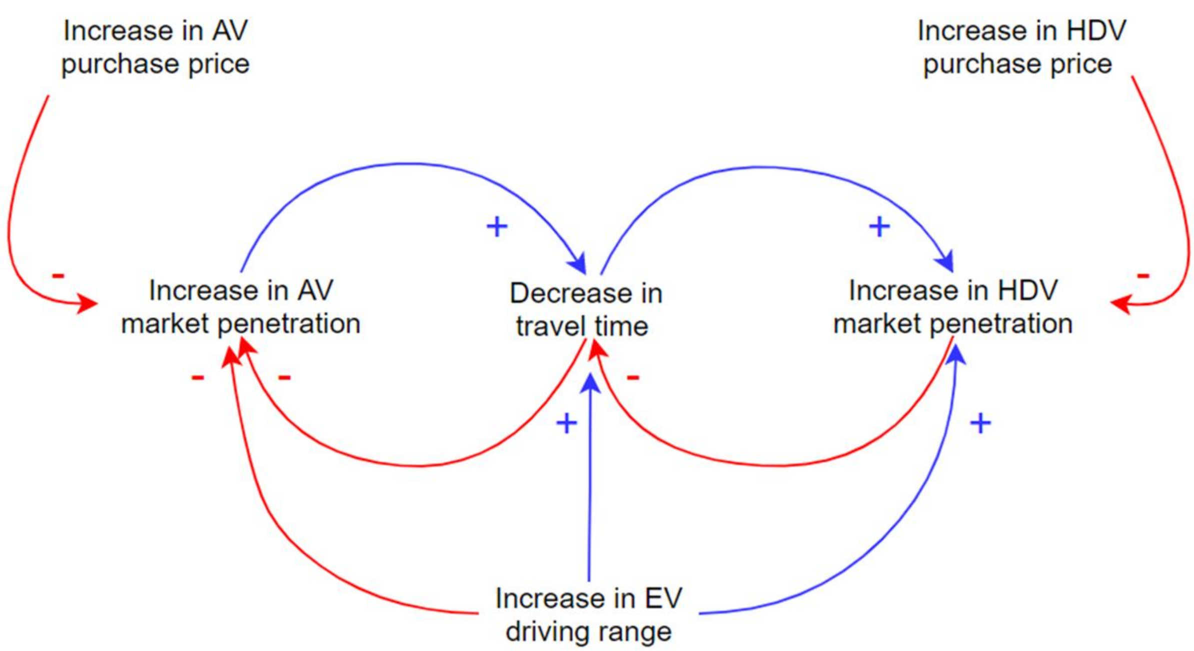



Figure 5-7. Impacts of factors on travel time and AV/HDV market penetration

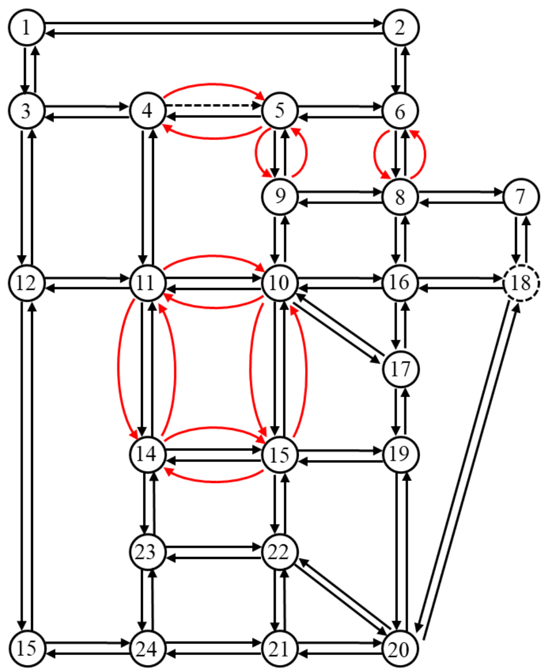
As shown in Table 5-5, the total cost, which is unweighted sum of construction and travel time costs, reduces as the level of EV charging facility investment (construction budget) increases. This is anticipated theoretically as an increase in the construction budget ($B$), i.e., the right-hand side of the equation (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 5-8 (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 facilities 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 5-8 (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 5-8 (c)), and the optimal solution prescribes construction of a level 1 charging station at node 18 and installation of a three 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.

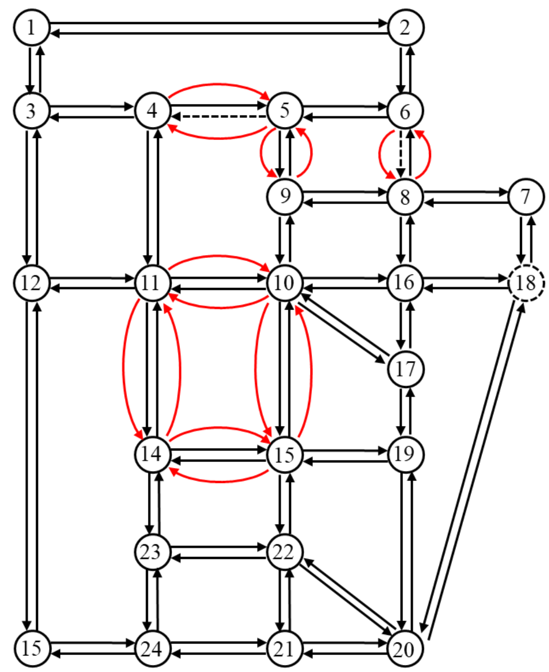
It is observed from the results that the model prioritizes the construction of wireless-charging facilities over constructing charging stations. This is intuitive because road users prefer recharging at wireless-charging lanes to avoid the extra recharging delay associated with charging stations. The results demonstrate that the higher level of EV charging facility investment (construction budget) can significantly reduce the charging delays and added travel time costs due to recharging at stations. Therefore, the transport decision-makers need to consider the trade-off between the level of EV charging facility investment and the monetary costs associated with the higher travel times. 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 of this infrastructure.

Table 5-5. Numerical results for different construction budget levels ($M)

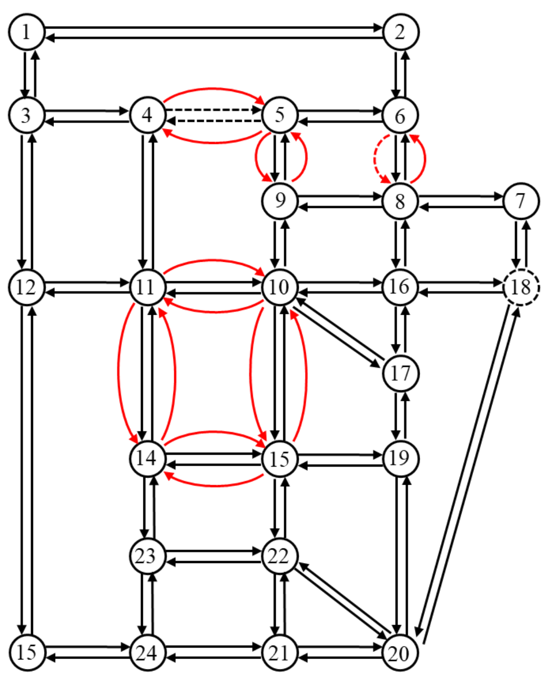
| Budget scenario | Construction budget | Construction cost | Total travel time cost | Total cost (unweighted sum) |
|---|---|---|---|---|
| Scenario 0 | 0.00 | 0.00 | 5.65 | 5.65 |
| Scenario 1 | 10.00 | 9.00 | 14.75 | 23.75 |
| Scenario 2 | 20.00 | 17.00 | 9.95 | 26.95 |
| Scenario 3 | 40.00 | 25.00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



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



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



(c) Scenario 3 (budget = $40 million)

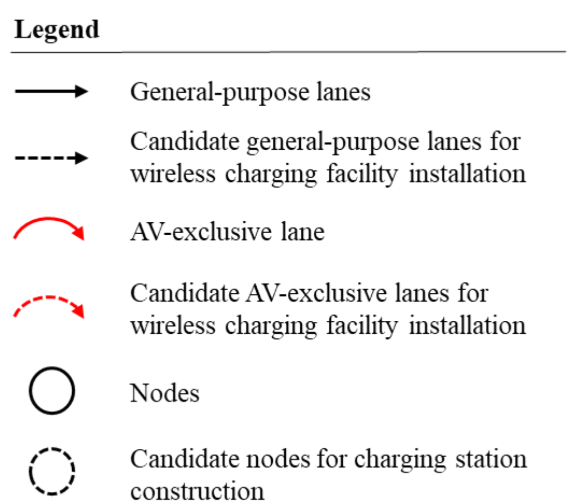



Figure 5-8. Optimal charging facility locations for different budget levels

Interestingly, as shown in Figure 5-9, it is observed that AV market share decreases slightly as the construction budget increases from scenario 1 to scenario 2. 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 prescribe 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 purchasing price of AV is higher compared to purchasing 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.

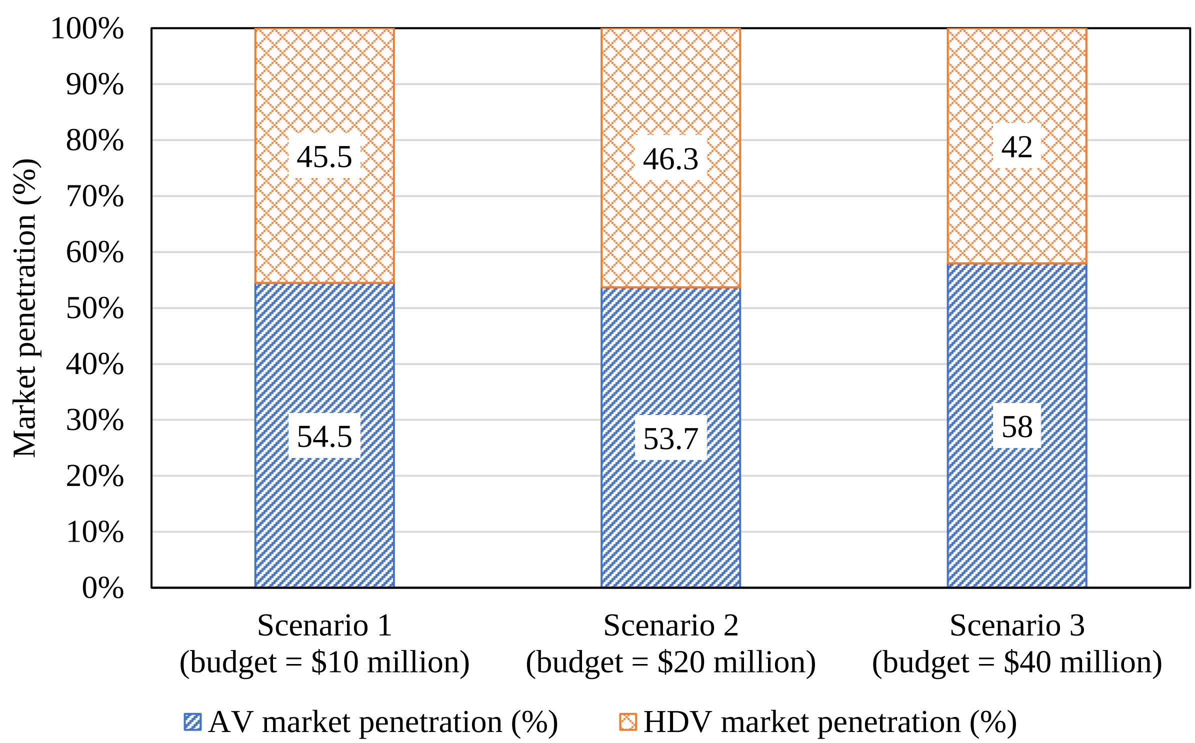



Figure 5-9. AV and HDV market penetration at different investment levels

## 5.7 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) at the optimal locations and the associated costs. In scenario

1, the transportation decision-makers intend to only provide wireless-charging facilities. In scenario 2, transportation decision-makers intend to only provide charging stations. In scenario 3, transportation decision-makers intend to provide both charging stations and wireless-charging facilities. Table 5-6 presents the charging method considered in each scenario.

Table 5-6. 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 5-10 presents a comparison of the results of the scenarios. Scenario 0 (presented in Figure 5-10) is the same as the scenario 0 presented in Section 5.6. 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 5-11 (a). In this scenario, all candidates selected for wireless-charging facility installation are located at general-purpose lanes. This result is intuitive because 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 Scenario 2 and 3. The charging delay for wireless-charging facilities 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 5-11 (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 5-11 (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 scenario 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 percent). 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.

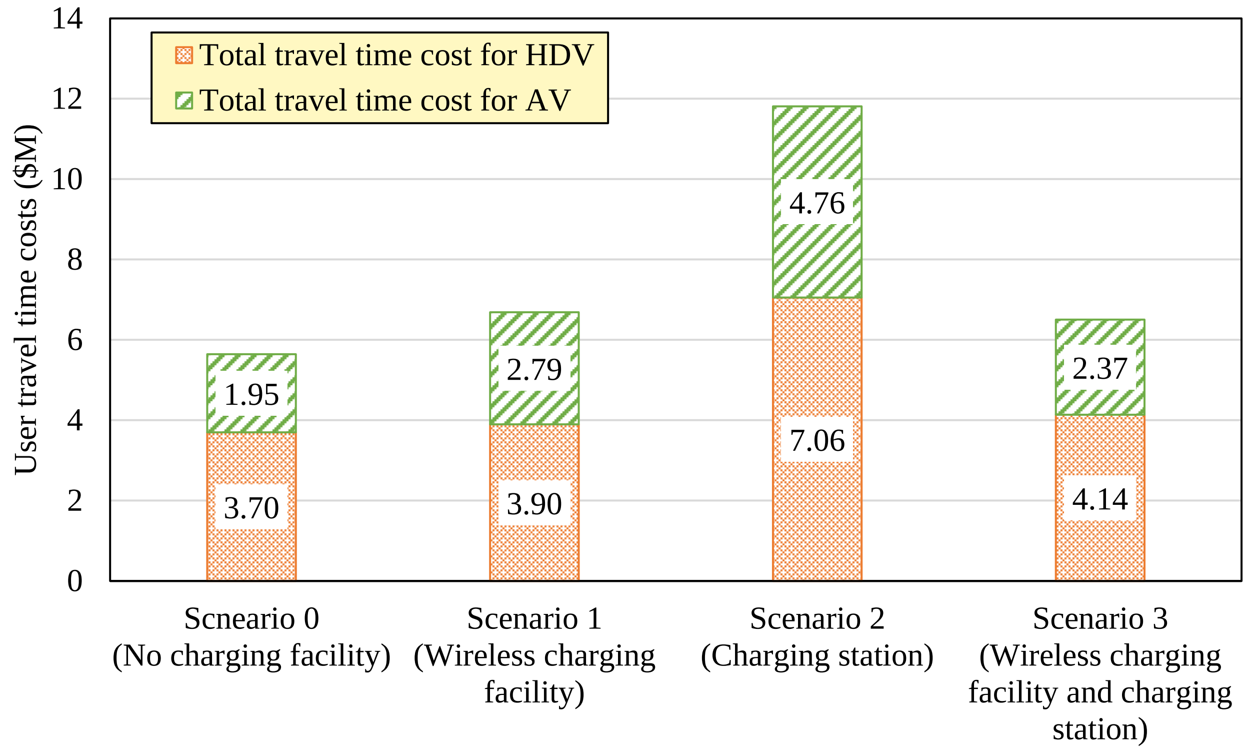
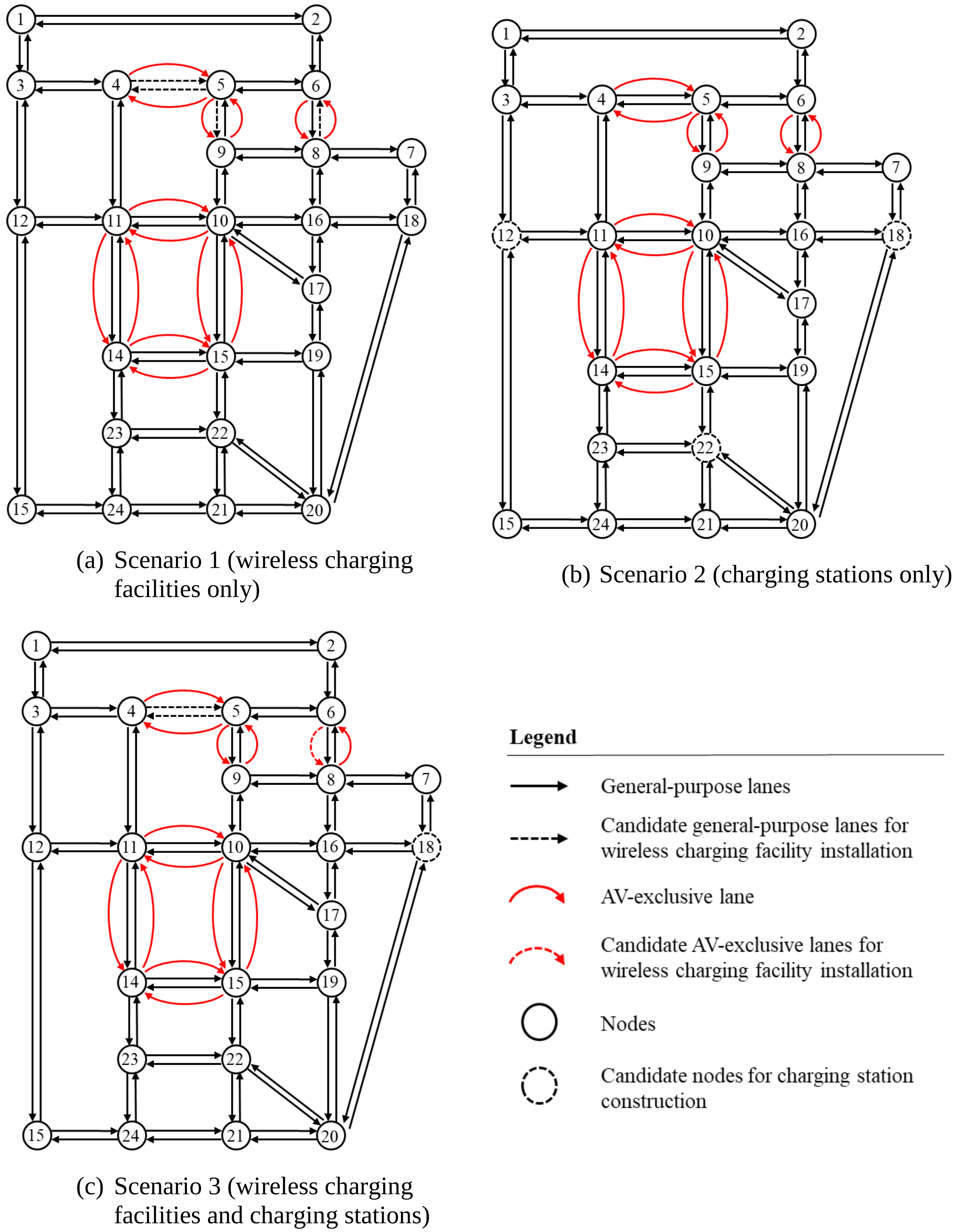



Figure 5-10. Comparison of the travel time cost of charging facility type scenarios




(a) Scenario 1 (wireless charging facilities only)

(b) Scenario 2 (charging stations only)

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

Figure 5-11. Optimal charging facility locations for charging facility type scenarios

## 5.8 Impacts of Lane Type Selection 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, which in scenario 1, transportation decision-makers intend to install wireless-charging facilities only at AV-exclusive lanes. In scenario 2, transportation decision-makers seek to install wireless-charging facilities only at general-purpose lanes, and in scenario 3, seek to install wireless-charging facilities at both AV-exclusive and general-purpose lanes. Table 5-7 presents lane type (AV-exclusive lane and/or general-purpose lane) considered for wireless charging facility installation for each scenario.

Table 5-7. Lane types for wireless charging facility installation scenarios

| Scenarios | Lane types |
|---|---|
| Scenario 1 | AV-exclusive lane |
| Scenario 2 | General-purpose lane |
| Scenario 3 | General-purpose lane and AV-exclusive lane |

Figure 5-12 compares the results of these scenarios. Scenario 0 presented in Figure 5-12 is the same as the scenario 0 presented in Section 5.6. 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 5-13 (a)). In this scenario, the model prescribes the construction of more charging stations compared to scenario 2 and 3, to meet the recharging needs of HDV users who cannot use wireless-charging facilities at AV-exclusive lanes. Therefore, a higher number of charging stations, as discussed earlier in Section 5.7, 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 this class of EV users. 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 5-13 (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 is intuitive because both charging stations and wireless-charging facilities are available for HDV users.

For scenario 3, as shown in Figure 5-13 (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.

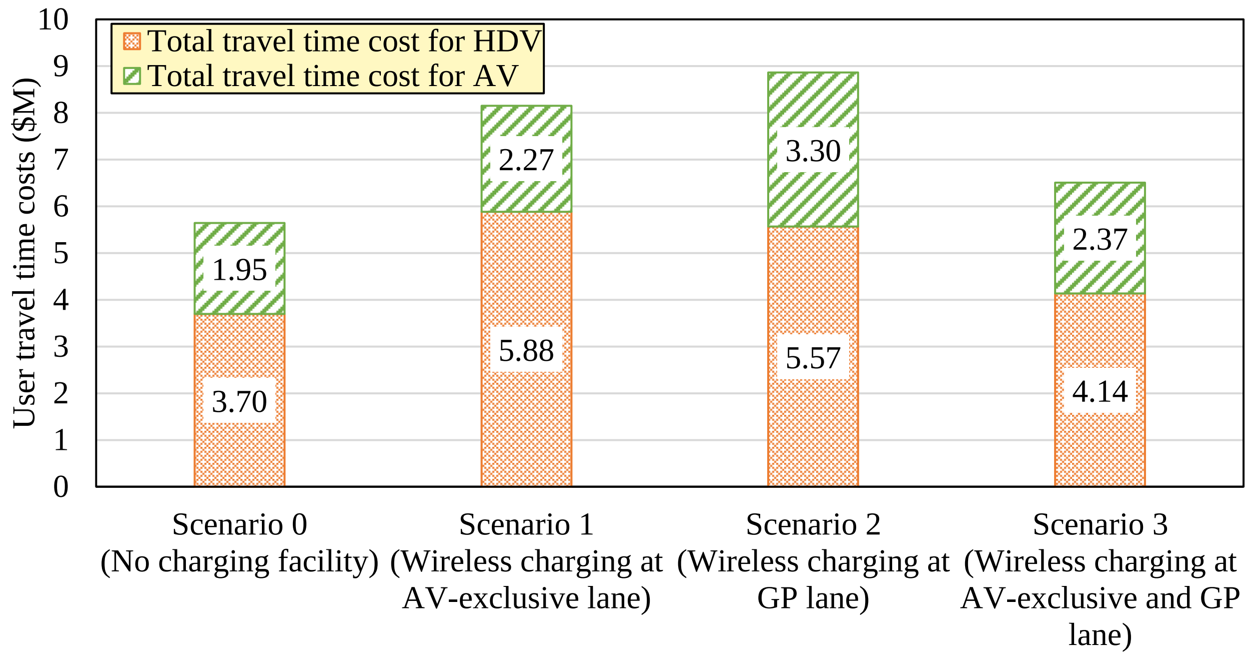
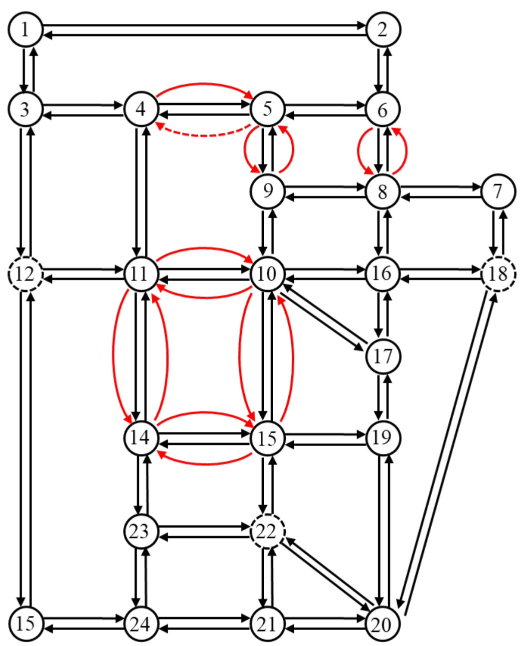
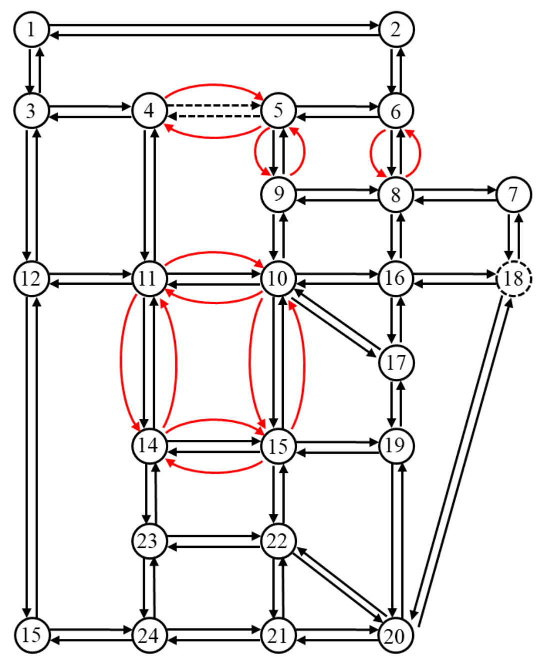


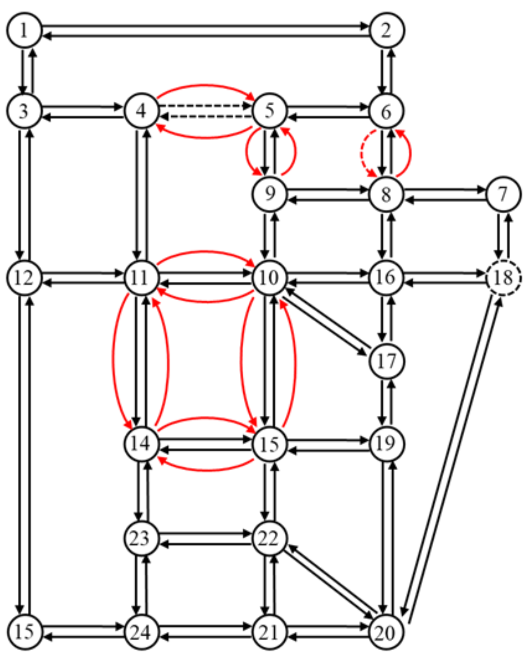

Figure 5-12. Comparison of results for lane type scenarios



(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)

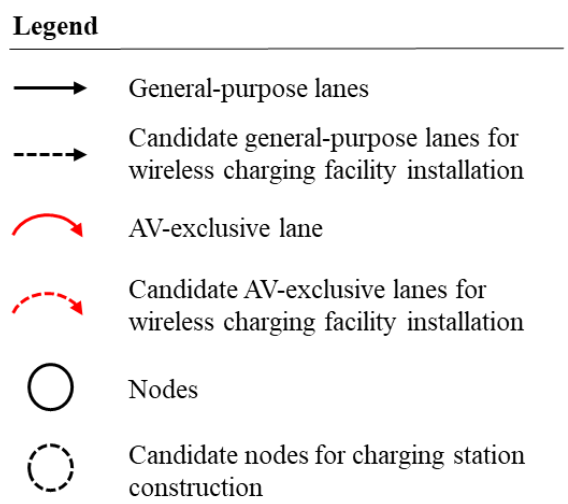



Figure 5-13. Optimal charging facility locations for lane type scenarios

## 5.9 Sensitivity Analysis on the AV Purchase Price

In this section, we investigate the impacts of AV purchasing price on AV market penetration. Consider three scenarios with different AV purchasing prices: scenario 1 with high AV purchasing price ($40,000), scenario 1 with medium AV purchasing price ($30,000), and scenario 1 with low AV purchasing price ($20,000). Table 5-8 presents the AV purchasing prices scenarios.

Table 5-8. AV purchasing price scenarios

| AV purchasing price scenarios | AV purchasing price |
|---|---|
| Scenario 1 | $40,000 |
| Scenario 2 | $30,000 |
| Scenario 3 | $20,000 |

Figure 5-14 illustrates the AV market penetration for different AV purchasing prices. In scenario 3, AV and HDV purchasing prices are assumed to be equal. In this scenario, the AV market penetration rate is 100%. This is an intuitive result because AV users' travel time is lower than that of HDV users and with same purchasing price, travelers prefer to purchase AVs rather than HDV. It is clear that by increasing the AV purchasing price the AV market penetration decreases, as shown in Figure 5-14.

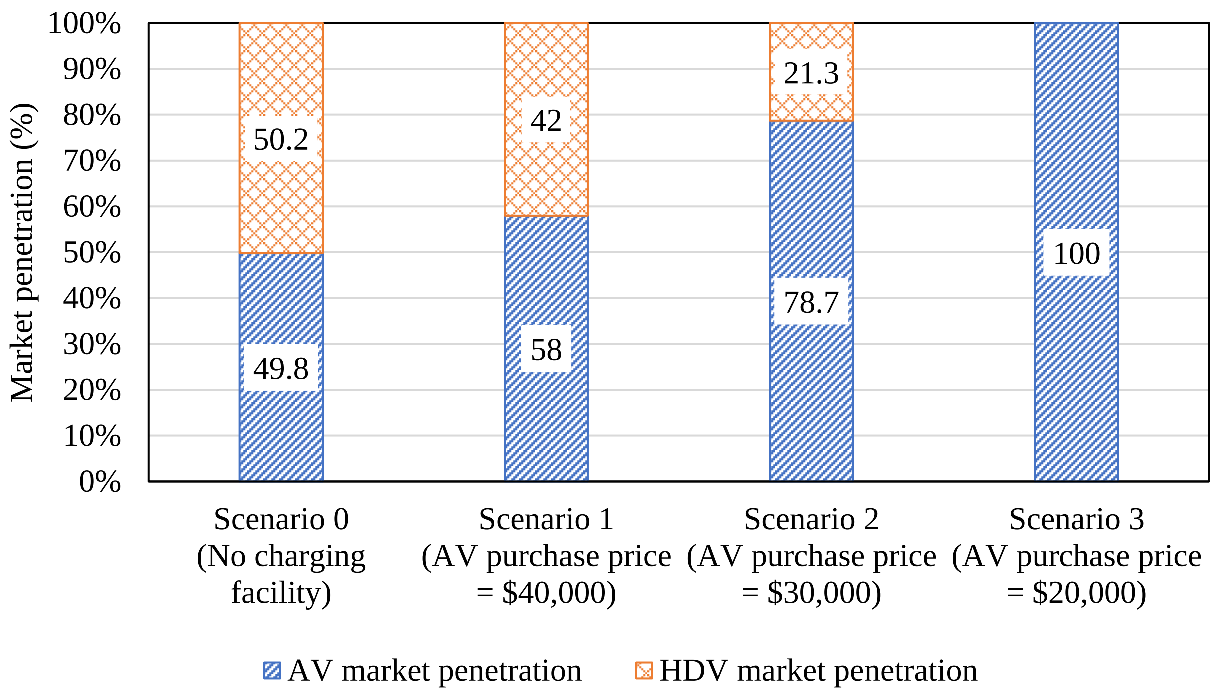



Figure 5-14. AV and HDV market penetration for the different AV purchase prices

Figure 5-15 compares the AV and HDV users' travel time cost for different AV purchasing price scenarios. The obtained results indicate that by decreasing the AV purchasing price, the total travel times cost decreases. This is because by decreasing AV purchasing 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 purchasing price decreases, the AV market share increases, results in total system travel time cost be mostly attributed to AVs rather than HDVs, which explains why AV users' travel time increases as AV purchasing price decreases.

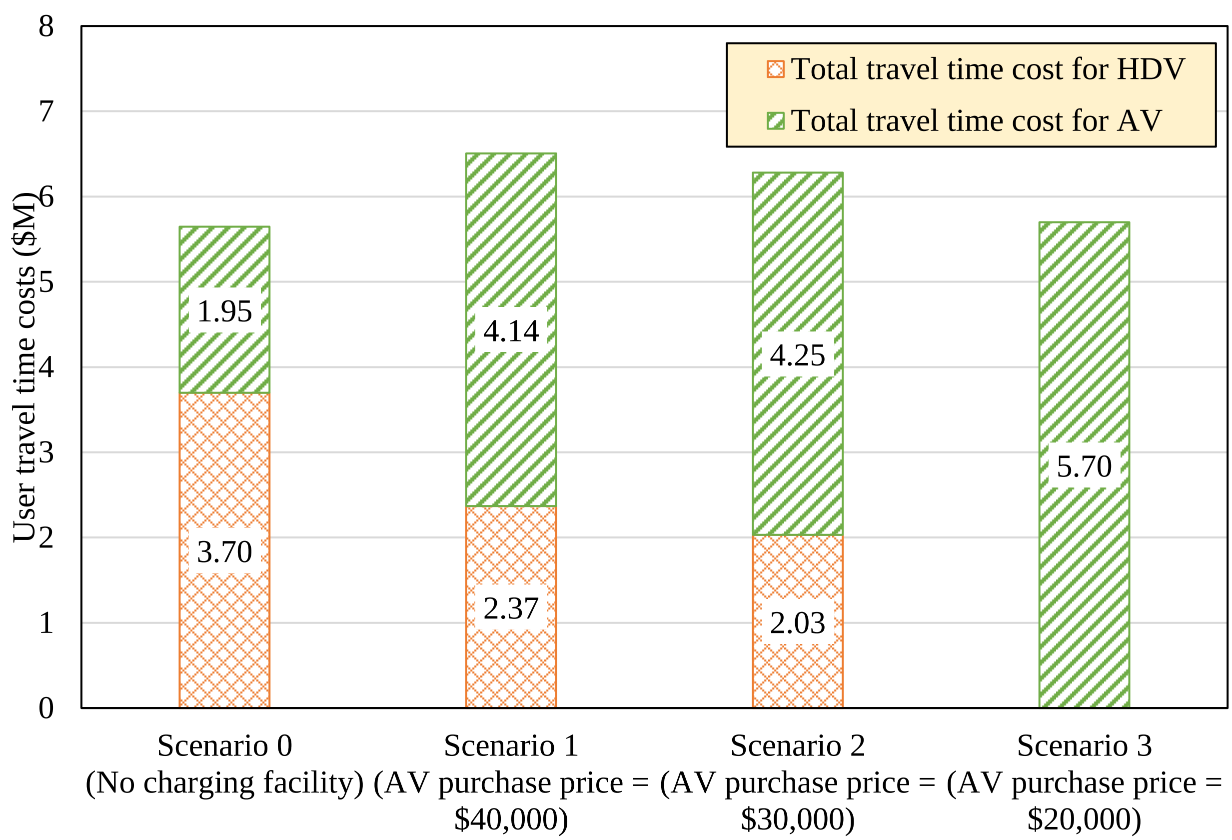



Figure 5-15. AV and HDV user travel time costs for different AV purchase prices

### 5.10 Sensitivity Analysis on the Driving Range

Finally, we investigate the impact of EV driving range on construction costs, total travel time costs, and the AV market penetration rate trend. It is important to carry out this analysis because as the

EV driving range is expected to increase due to technological advancements (Zakaria et al., 2019). It is assumed that the EV driving range increases from 10 miles to 20 miles over the planning phase. Figure 5-16 presents the numerical results for different EV driving ranges. The results suggest that construction cost and total travel time cost are reduced by increasing the 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.

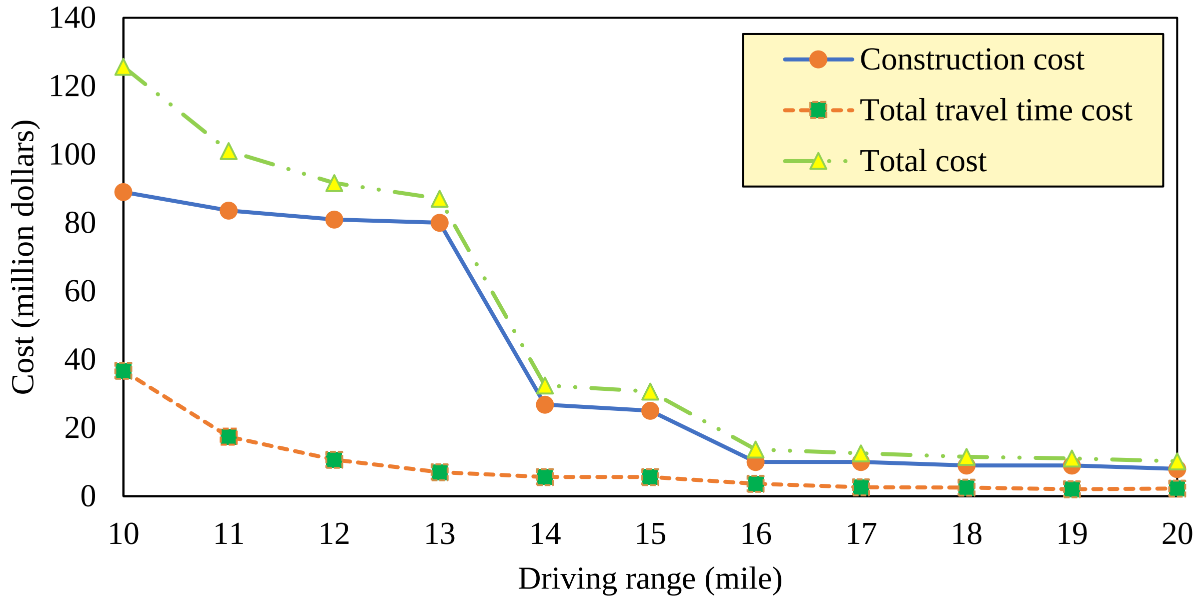



Figure 5-16. Impact of EV initial driving range on costs

The impact of driving range on the AV market penetration was investigated. Figure 5-17 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 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, high driving ranges eliminate charging delay. As a result, difference of travel time for AV and HDV decreases. Since the purchasing 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 5.6).

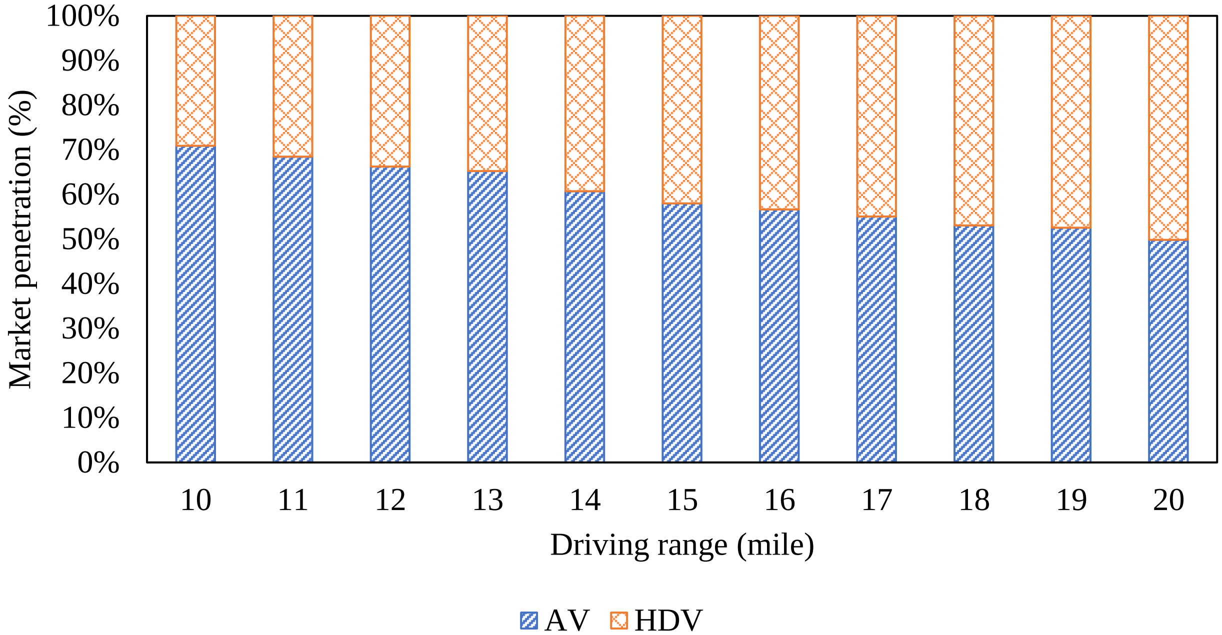



Figure 5-17. Impact of EV initial driving range on AVs market penetration.

### 5.11 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 5.2, and the obtained base analyses were discussed in following Section 5.3. 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, multiple types of EV charging facilities, lane type, EV driving range, and AV purchasing price. A tradeoff between investment and EV charging facility construction is obtained. Obtained results suggested that with increasing the EV charging facility investment, model decides to install more wireless-charging facilities rather than charging stations. Furthermore, the sensitivity analyses indicated that provision of multiple types of EV charging facilities and enabling both AV-exclusive and general-purpose lanes for wireless-charging facility installation reduces the total cost significantly. Finally, the impacts of EV driving range and AV purchasing price on AV market share is discussed in detail.

# 6. CONCLUDING REMARKS

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

## 6.1 Summary

The main objective of the thesis is to provide a comprehensive framework to determine the locations and capacities of charging facilities 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. The transportation decision-makers at the upper-level model seek to minimize the total travel time cost and construction cost. The transportation decision-makers' decision-making variables are the location of EV charging facilities and operating capacity. These decision variables are subject to the budgetary limitations. In the lower-level model, travelers vehicle type (AV vs. HDV) choice is modeled using a utility-based logit model. The utility function consists of a weighted sum of travel time for each origin-destination pair and the purchasing price of the vehicles. Travelers seek to minimize their travel time. It is assumed that the transportation decision-makers provide AV-exclusive lanes to promote AV usage and, ultimately, to reduce the total travel time cost.

## 6.2 Findings and Conclusions

The proposed framework was tested using the Sioux-Falls road network. The numerical experiments suggested that if the transport 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 facility installation rather than the construction of charging stations. It is also found 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.

Further, the results suggest that, compared to the scenario where the transport decision-makers construct charging stations and where construct wireless-charging facilities, the scenario where the transport decision-makers construct both of them, 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 cost savings. 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 are provided only at general-purpose lanes, respectively. Finally, analyses of the vehicles' driving range confirmed that travelers need to recharge more in the scenario of low driving range. As a result, travelers experience more charging delay and also, they need to deviate often from their optimal routes leading to higher travel times. This leads to higher market penetration of AVs because AVs typically have lower travel times compared to HDVs and as a result, travelers prefer purchasing AV rather than HDV. On the other hand, with increasing the EV driving range, the recharging need decreases, and as a result, recharging delay and total travel time cost decrease. This decreases the AV market penetration because the AV purchase price is higher than HDV purchase price and travelers prefer to purchase HDV rather than AV.

## 6.3 Limitations of the Study

One limitation of this thesis is that the mixed fleet of AV and HDV is considered to be electric. Although the literature suggests that future AVs will most likely be electric (Lam et al., 2018), AVs can also be Alternative Fuel Vehicle (AFV). Another limitation of this thesis is that AV-exclusive lane locations are considered to be established as a part of the problem setting and therefore is not variable. Although the optimal locations for AV-exclusive lane on the Sioux Falls road network identified by Chen et al. (2019) is used in the analysis, the proposed model does not capture the effect of the AV-exclusive lanes' optimal locations on the EV charging facility location problem. 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 thesis is that it did not consider different performance attributes of AVs and HDVs in the vehicle type purchase model, such as the safety benefits of AVs.

Furthermore, this study did not consider shared AVs. Although some researchers believe that most AVs will be private in the future (Correia & van Arem, 2016; Saeed et al., 2020), shared AVs will also represent a significant proportion of AVs (Overtoom et al., 2020), and their charging needs may differ from those of private AVs. Another limitation of this thesis 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 availability 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 price. In the early phases of AV operations, AV-exclusive lane deployment benefits will most likely be earned by wealthier segments of the population.

## 6.4 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 thesis. 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 the thesis's limitation of considering full EV adoption, but it also allows agencies to be better equipped to assess the scheduling of constructing EV charging facilities over the planning horizon. Second, while we investigated the effects of AV-exclusive links, the location of AV-exclusive links is assumed to be fixed in this thesis. Future research could develop a model that considers the location of AV-exclusive lanes to be variable. Third, more research on shared AVs is needed to understand the comprehensive impact of AVs on transportation network. Fourth, the Sioux-Falls road network, which is a small network, is used to test the proposed framework. Larger networks may be considered in future studies to test the proposed framework. Finally, battery swapping (Gao et al.,

2020) can be considered as a third option for EV charging modes, and could possibly contribute to solving the wider problem of the EV charging facility planning.

# REFERENCES


Abareshi, M., & Zaferanieh, M. (2019). A bi-level capacitated P-median facility location problem with the most likely allocation solution. *Transportation Research. Part B: Methodological*, *123*, 1–20. https://doi.org/10.1016/j.trb.2019.03.013

Adler, J. D., & Mirchandani, P. B. (2014). Online routing and battery reservations for electric vehicles with swappable batteries. *Transportation Research Part B: Methodological*, *70*, 285–302. https://doi.org/https://doi.org/10.1016/j.trb.2014.09.005

Alavidoost, M. H., Tarimoradi, M., & Zarandi, M. H. F. (2018). Bi-objective Mixed-integer Nonlinear Programming for Multi-commodity Tri-echelon Supply Chain Networks. *Journal of Intelligent Manufacturing*, *29*(4), 809–826. https://doi.org/10.1007/s10845-015-1130-9

Amjad, M., Ahmad, A., Rehmani, M. H., & Umer, T. (2018). A review of EVs charging: From the perspective of energy optimization, optimization approaches, and charging techniques. *Transportation Research Part D: Transport and Environment*, *62*, 386–417. https://doi.org/10.1016/j.trd.2018.03.006

Arem, B. van, Driel, C. J. G. van, & Visser, R. (2006). The Impact of Cooperative Adaptive Cruise Control on Traffic-Flow Characteristics. *IEEE Transactions on Intelligent Transportation Systems*, *7*(4), 429–436. https://doi.org/10.1109/TITS.2006.884615

Arslan, O., & Karaşan, O. E. (2016). A Benders decomposition approach for the charging station location problem with plug-in hybrid electric vehicles. *Transportation Research Part B: Methodological*, *93*, 670–695. https://doi.org/10.1016/J.TRB.2016.09.001

Arvin, R., Khattak, A. J., Kamrani, M., & Rio-torres, J. (2021). Safety evaluation of connected and automated vehicles in mixed traffic with conventional vehicles at intersections. *Journal of Intelligent Transportation Systems*, *25*(2), 170–187. https://doi.org/10.1080/15472450.2020.1834392

Ashkrof, P., Homem de Almeida Correia, G., & van Arem, B. (2020). Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in the Netherlands. *Transportation Research Part D: Transport and Environment*, *78*, 102206. https://doi.org/10.1016/j.trd.2019.102206

Bahrami, S., Ashtiani, H. Z., Nourinejad, M., & Roorda, M. J. (2017). A complementarity equilibrium model for electric vehicles with charging. *International Journal of Transportation Science and Technology*, *6*(4), 255–271. https://doi.org/10.1016/j.ijtst.2017.05.007

Bai, Q., Ahmed, A., Li, Z., & Labi, S. (2015). A hybrid pareto frontier generation method for trade-off analysis in transportation asset management. *Computer-Aided Civil and Infrastructure Engineering*, *30*(3), 163–180. https://doi.org/10.1111/mice.12079

Bai, Q., Labi, S., & Li, Z. (2008). Trade-off Analysis Methodology for Asset Management. In *JTRP Technical Reports*. Joint Transportation Research Program. https://doi.org/10.5703/1288284314305

Bai, Q., Labi, S., & Sinha, K. C. (2012). Trade-Off Analysis for Multiobjective Optimization in Transportation Asset Management by Generating Pareto Frontiers Using Extreme Points Nondominated Sorting Genetic Algorithm II. *Journal of Transportation Engineering*, *138*(6), 798–808. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000369.

Barth, H., Jung, M., Braun, M., Schmuelling, B., Schmülling, B., & Reker, U. (2011). Concept evaluation of an inductive charging system for electric vehicles. In *researchgate.net* (Vol. 10). https://www.researchgate.net/publication/266053228

Bateman, D., Leal, D., Reeves, S., Emre, M., Stark, L., Myers, R., & Lamb, M. (2018). *TRL ACADEMY REPORT PPR875 Electric Road Systems: a solution for the future*. https://www.trafikverket.se/contentassets/2d8f4da1602a497b82ab6368e93baa6a/piarc_elvag.pdf

Bauer, C., Hofer, J., Althaus, H.-J., Del Duce, A., & Simons, A. (2015). The environmental performance of current and future passenger vehicles: Life cycle assessment based on a novel scenario analysis framework. *Applied Energy*, *157*, 871–883. https://doi.org/https://doi.org/10.1016/j.apenergy.2015.01.019

Bazaraa, M. S., Sherali, H. D., & Shetty, C. M. (2013). *Nonlinear Programming: Theory and Algorithms*. John Wiley & Sons.

Bellman, R. (1958). On a routing problem. *Quarterly of Applied Mathematics*, *16*(1), 87–90. https://doi.org/10.1090/qam/102435

Berliner, R. M., Hardman, S., & Tal, G. (2019). Uncovering early adopter's perceptions and purchase intentions of automated vehicles: Insights from early adopters of electric vehicles in California. *Transportation Research Part F: Traffic Psychology and Behaviour*, *60*, 712–722. https://doi.org/https://doi.org/10.1016/j.trf.2018.11.010

Bernecker, T., Hasselgren, B., Helms, H., Speiser, J., & Widegren, F. (2020). *Business Models, Ownership, and Financing Strategies Implications of the introduction of electric road systems on markets and possible business models Final Report*. http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-414181

Biresselioglu, M. E., Demirbag Kaplan, M., & Yilmaz, B. K. (2018). Electric mobility in Europe: A comprehensive review of motivators and barriers in decision making processes. *Transportation Research Part A: Policy and Practice*, *109*, 1–13. https://doi.org/https://doi.org/10.1016/j.tra.2018.01.017

Cavadas, J., Homem de Almeida Correia, G., & Gouveia, J. (2015). A MIP model for locating slow-charging stations for electric vehicles in urban areas accounting for driver tours. *Transportation Research Part E: Logistics and Transportation Review*, *75*, 188–201. https://doi.org/10.1016/J.TRE.2014.11.005

Ceylan, H., & Bell, M. G. H. (2005). Genetic algorithm solution for the stochastic equilibrium transportation networks under congestion. *Transportation Research Part B: Methodological*, *39*(2), 169–185. https://doi.org/https://doi.org/10.1016/j.trb.2004.04.001

Chau, K. T., & Chan, C. C. (2007). Emerging Energy-Efficient Technologies for Hybrid Electric Vehicles. *Proceedings of the IEEE*, *95*(4), 821–835. https://doi.org/10.1109/JPROC.2006.890114

Chen, S., Wang, H., & Meng, Q. (2019). Designing autonomous vehicle incentive program with uncertain vehicle purchase price. *Transportation Research Part C: Emerging Technologies*, *103*(April), 226–245. https://doi.org/10.1016/j.trc.2019.04.013

Chen, T. D., Kockelman, K. M., & Khan, M. (2013). Locating Electric Vehicle Charging Stations. *Transportation Research Record: Journal of the Transportation Research Board*, *2385*(1), 28–36. https://doi.org/10.3141/2385-04

Chen, T., Zhang, X. P., Wang, J., Li, J., Wu, C., Hu, M., & Bian, H. (2020). A Review on Electric Vehicle Charging Infrastructure Development in the UK. *Journal of Modern Power Systems and Clean Energy*, *8*(2), 193–205. https://doi.org/10.35833/MPCE.2018.000374

Chen, Z. (2016). Optimal deployment of charging lanes for electric vehicles in transportation networks. *Transportation Research Part B: Methodological*, *91*, 344–365. https://doi.org/https://doi.org/10.1016/j.trb.2016.05.018

Chen, Z., He, F., Zhang, L., & Yin, Y. (2016). Optimal deployment of autonomous vehicle lanes with endogenous market penetration. *Transportation Research Part C: Emerging Technologies*, *72*, 143–156. https://doi.org/10.1016/J.TRC.2016.09.013

Correia, G. H. de A., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. *Transportation Research Part A: Policy and Practice*, *119*, 359–382. https://doi.org/10.1016/j.tra.2018.11.016

Correia, G. H. de A., & van Arem, B. (2016). Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. *Transportation Research Part B: Methodological*, *87*, 64–88. https://doi.org/https://doi.org/10.1016/j.trb.2016.03.002

Council, E. (2014). 2030 Climate and Energy Policy Framework. *European Council, Brussels, October*, 1–15. http://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/ec/145397.pdf

Covic, Grant A., & Boys, J. T. (2013). Inductive power transfer. *Proceedings of the IEEE*, *101*(6), 1276–1289. https://doi.org/10.1109/JPROC.2013.2244536

Covic, Grant Anthony, & Boys, J. T. (2013). Modern trends in inductive power transfer for transportation applications. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, *1*(1), 28–41. https://doi.org/10.1109/JESTPE.2013.2264473

Cyganski, R., Fraedrich, E., & Lenz, B. (2015). *Travel-time valuation for automated driving: A use-case-driven study*. https://www.researchgate.net/profile/Rita_Cyganski/publication/273383058_Travel-time_valuation_for_automated_driving_A_use-case-driven_study/links/54fffd670cf2eaf210bcd82e/Travel-time-valuation-for-automated-driving-A-use-case-driven-study.pdf

de Almeida Correia, G. H., & Gonçalves Santos, R. F. (2014). Optimizing the Use of Electric Vehicles in a Regional Car Rental Fleet. *Transportation Research Record: Journal of the Transportation Research Board*, *2454*(1), 76–83. https://doi.org/10.3141/2454-10

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

Domínguez-Navarro, J. A., Dufo-López, R., Yusta-Loyo, J. M., Artal-Sevil, J. S., & Bernal-Agustín, J. L. (2019). Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems. *International Journal of Electrical Power and Energy Systems*, *105*, 46–58. https://doi.org/10.1016/j.ijepes.2018.08.001

Dong, J., Chen, S., Ha, P. Y. J., Li, Y., & Labi, S. (2020). *A DRL-based Multiagent Cooperative Control Framework for CAV Networks: a Graphic Convolution Q Network, preprints,*. http://arxiv.org/abs/2010.05437

Duarte, F., & Ratti, C. (2018). The Impact of Autonomous Vehicles on Cities: A Review. *Journal of Urban Technology*, *25*(4), 3–18. https://doi.org/10.1080/10630732.2018.1493883

ECE. (2015). *Proposal for an Electric Vehicle Regulatory Reference Guide, ECE /TRANS/WP.29/GRPE/2014/13*. *2016*(March), 40. https://www.unece.org/fileadmin/DAM/trans/doc/2014/wp29grpe/ECE-TRANS-WP29-GRPE-%0A2014-13e.pdf.

EPA. (2015). *Sources of Greenhouse Gas Emissions, US EPA.* https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167–181. https://doi.org/https://doi.org/10.1016/j.tra.2015.04.003

FHWA. (2016). *The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations*. https://www.transportation.gov/sites/dot.gov/files/docs/2016 Revised Value of Travel Time Guidance.pdf

Frade, I., Ribeiro, A., Gonçalves, G., & Antunes, A. P. (2011). Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. *Transportation Research Record: Journal of the Transportation Research Board*, *2252*(1), 91–98. https://doi.org/10.3141/2252-12

Frank, M., & Wolfe, P. (1956). Algorithm for quadratic programming. *Naval Research Logistics Quarterly*, *3*(1–2), 95–110.

Fuller, M. (2016). Wireless charging in California: Range, recharge, and vehicle electrification. *Transportation Research Part C: Emerging Technologies*, *67*, 343–356. https://doi.org/10.1016/j.trc.2016.02.013

Gao, Y., Yang, J., Yang, M., & Li, Z. (2020). Deep Reinforcement Learning Based Optimal Schedule for a Battery Swapping Station Considering Uncertainties. *IEEE Transactions on Industry Applications*, *56*(5), 5775–5784. https://doi.org/10.1109/TIA.2020.2986412

García-Villalobos, J., Zamora, I., San Martín, J. I., Asensio, F. J., & Aperribay, V. (2014). Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches. In *Renewable and Sustainable Energy Reviews* (Vol. 38, pp. 717–731). Elsevier Ltd. https://doi.org/10.1016/j.rser.2014.07.040

Ghamami, M., Kavianipour, M., Zockaie, A., Hohnstadt, L. R., & Ouyang, Y. (2020). Refueling infrastructure planning in intercity networks considering route choice and travel time delay for mixed fleet of electric and conventional vehicles. *Transportation Research Part C: Emerging Technologies*, *120*, 102802. https://doi.org/https://doi.org/10.1016/j.trc.2020.102802

Ghamami, M., Zockaie, A., & Nie, Y. M. (2016). A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel. *Transportation Research Part C: Emerging Technologies*, *68*, 389–402. https://doi.org/10.1016/j.trc.2016.04.016

Gharaibeh, N. G., Chiu, Y.-C., & Gurian, P. L. (2006). Decision Methodology for Allocating Funds across Transportation Infrastructure Assets. *Journal of Infrastructure Systems*, *12*(1), 1–9. https://doi.org/10.1061/(ASCE)1076-0342(2006)12:1(1)

Ghosh, A. (2020). Possibilities and challenges for the inclusion of the electric vehicle (EV) to reduce the carbon footprint in the transport sector: A review. *Energies*, *13*(10). https://doi.org/10.3390/en13102602

Gill, J. S., Bhavsar, P., Chowdhury, M., Johnson, J., Taiber, J., & Fries, R. (2014). Infrastructure cost issues related to inductively coupled power transfer for electric vehicles. *Procedia Computer Science*, *32*, 545–552. https://doi.org/10.1016/j.procs.2014.05.459

González-González, E., Nogués, S., & Stead, D. (2019). Automated vehicles and the city of tomorrow: A backcasting approach. *Cities*, *94*, 153–160. https://doi.org/https://doi.org/10.1016/j.cities.2019.05.034

Ha, P. (2019). *Sustainability Considerations for Optimal Autonomous Vehicle Lane Deployment*. M.S.Thesis, Purdue University, West Lafayette, IN. https://doi.org/10.25394/PGS.11303099.V1

Ha, P., Chen, S., Dong, J., Du, R., Li, Y., & Labi, S. (2020). Leveraging the capabilities of connected and Autonomous vehicles and multi-agent reinforcement learning to mitigate highway bottleneck congestion, preprint,. In *arXiv*.

Ha, P., Chen, S., Du, R., Dong, J., Li, Y., & Labi, S. (2020). Vehicle Connectivity and Automation: A Sibling Relationship. *Frontiers in Built Environment*, *6*, 1–12. https://doi.org/10.3389/fbuil.2020.590036

Haddad, Di., Konstantinou, T., Prasad, A., Hua, Z., Aliprantis, Di., Gkritza, K., & Pekarek, S. (2019). Data-Driven Design and Assessment of Dynamic Wireless Charging Systems. *2019 IEEE PELS Workshop on Emerging Technologies: Wireless Power Transfer, WoW 2019*, 59–64. https://doi.org/10.1109/WoW45936.2019.9030612

Hardman, S., Berliner, R., & Tal, G. (2019). Who will be the early adopters of automated vehicles? Insights from a survey of electric vehicle owners in the United States. *Transportation Research Part D: Transport and Environment*, *71*, 248–264. https://doi.org/https://doi.org/10.1016/j.trd.2018.12.001

He, F., Yin, Y., & Zhou, J. (2013). Integrated pricing of roads and electricity enabled by wireless power transfer. *Transportation Research Part C: Emerging Technologies*, *34*, 1–15. https://doi.org/https://doi.org/10.1016/j.trc.2013.05.005

He, J., Yang, H., Huang, H. J., & Tang, T. Q. (2018). Impacts of wireless charging lanes on travel time and energy consumption in a two-lane road system. *Physica A: Statistical Mechanics and Its Applications*, *500*, 1–10. https://doi.org/10.1016/j.physa.2018.02.074

Hobbs, B. F., & Meier, P. (2000). *Introduction* (pp. 1–14). https://doi.org/10.1007/978-1-4615-4477-7_1

Hoogendoorn, R., van Arem, B., & Hoogendoom, S. (2014). Automated Driving, Traffic Flow Efficiency, and Human Factors: Literature Review. *Transportation Research Record*, *2422*(1), 113–120. https://doi.org/10.3141/2422-13

Hosseini, M., & MirHassani, S. A. (2015). Refueling-station location problem under uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, *84*, 101–116. https://doi.org/10.1016/J.TRE.2015.10.009

Hosseininasab, S.-M., & Shetab-Boushehri, S.-N. (2015). Integration of Selecting and Scheduling Urban Road Construction Projects as a Time-dependent Discrete Network Design Problem. *European Journal of Operational Research*, *246*(3), 762–771. https://doi.org/10.1016/J.EJOR.2015.05.039

Hosseininasab, S.-M., Shetab-Boushehri, S.-N., Hejazi, S. R., & Karimi, H. (2018). A Multi-objective Integrated Model for Selecting, Scheduling, and Budgeting Road Construction Projects. *European Journal of Operational Research*, *271*(1), 262–277. https://doi.org/10.1016/J.EJOR.2018.04.051

Huang, Y., Li, S., & Qian, Z. S. (2015). Optimal Deployment of Alternative Fueling Stations on Transportation Networks Considering Deviation Paths. *Networks and Spatial Economics*, *15*(1), 183–204. https://doi.org/10.1007/s11067-014-9275-1

IEA. (2017). *Energy Technology Perspectives 2017, IEA, Paris*. https://www.iea.org/reports/energy-technology-perspectives-2017

Jia, L., Hu, Z., Liang, W., Lang, W., & Song, Y. (2014). A novel approach for urban electric vehicle charging facility planning considering combination of slow and fast charging. *POWERCON 2014 - 2014 International Conference on Power System Technology: Towards Green, Efficient and Smart Power System, Proceedings*, 3354–3360. https://doi.org/10.1109/POWERCON.2014.6993928

Jochem, P., Babrowski, S., & Fichtner, W. (2015). Assessing CO2 emissions of electric vehicles in Germany in 2030. *Transportation Research Part A: Policy and Practice*, *78*, 68–83. https://doi.org/https://doi.org/10.1016/j.tra.2015.05.007

Ko, Y. D., & Jang, Y. J. (2013). The Optimal System Design of the Online Electric Vehicle Utilizing Wireless Power Transmission Technology. *IEEE Transactions on Intelligent Transportation Systems*, *14*(3), 1255–1265. https://doi.org/10.1109/TITS.2013.2259159

Kopelias, P., Demiridi, E., Vogiatzis, K., Skabardonis, A., & Zafiropoulou, V. (2020). Connected & autonomous vehicles – Environmental impacts – A review. *Science of The Total Environment*, *712*, 135237. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.135237

Labi, S. (2014). *Introduction to Civil Engineering Systems: A Systems Perspective to the Development of Civil Engineering Facilities*. Wiley.

Lam, A. Y. S., Yu, J. J. Q., Hou, Y., & Li, V. O. K. (2018). Coordinated Autonomous Vehicle Parking for Vehicle-to-Grid Services: Formulation and Distributed Algorithm. *IEEE Transactions on Smart Grid*, *9*(5), 4356–4366. https://doi.org/10.1109/TSG.2017.2655299

Lamptey, G., Ahmad, M., & Labi, S. (2005). Life Cycle Cost Analysis for INDOT Pavement Design Procedures. In *JTRP Technical Reports*. Joint Transportation Research Program. https://doi.org/10.5703/1288284313261

LeBlanc, L. J., Morlok, E. K., & Pierskalla, W. P. (1975). An Efficient Approach to Solving the Road Network Equilibrium Traffic Assignment Problem. *Transportation Research*, *9*(5), 309–318. https://doi.org/10.1016/0041-1647(75)90030-1

Lee, C., & Han, J. (2017). Benders-and-Price approach for electric vehicle charging station location problem under probabilistic travel range. *Transportation Research Part B: Methodological*, *106*, 130–152. https://doi.org/https://doi.org/10.1016/j.trb.2017.10.011

Li, S., Huang, Y., & Mason, S. J. (2016). A multi-period optimization model for the deployment of public electric vehicle charging stations on network. *Transportation Research Part C: Emerging Technologies*, *65*, 128–143. https://doi.org/10.1016/j.trc.2016.01.008

Liang, X., Correia, G. H. de A., & van Arem, B. (2016). Optimizing the service area and trip selection of an electric automated taxi system used for the last mile of train trips. *Transportation Research Part E: Logistics and Transportation Review*, *93*, 115–129. https://doi.org/https://doi.org/10.1016/j.tre.2016.05.006

Lin, C.-C., & Lin, C.-C. (2018). The p-center flow-refueling facility location problem. *Transportation Research. Part B: Methodological*, *118*, 124–142. https://doi.org/10.1016/j.trb.2018.10.008

Liu, H., & Wang, D. Z. W. (2017). Locating multiple types of charging facilities for battery electric vehicles. *Transportation Research Part B: Methodological*, *103*, 30–55. https://doi.org/10.1016/j.trb.2017.01.005

Liu, Z., & Song, Z. (2019). Strategic planning of dedicated autonomous vehicle lanes and autonomous vehicle/toll lanes in transportation networks. *Transportation Research Part C: Emerging Technologies*, *106*, 381–403. https://doi.org/https://doi.org/10.1016/j.trc.2019.07.022

Mazloumi, E., Mesbah, M., Ceder, A., Moridpour, S., & Currie, G. (2012). Efficient Transit Schedule Design of timing points: A comparison of Ant Colony and Genetic Algorithms. *Transportation Research Part B: Methodological*, *46*(1), 217–234. https://doi.org/https://doi.org/10.1016/j.trb.2011.09.010

Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2009). Facility location and supply chain management – A review. *European Journal of Operational Research*, *196*(2), 401–412. https://doi.org/https://doi.org/10.1016/j.ejor.2008.05.007

Metz, B., Davidson, O., Bosch, P., Dave, R., & Meyer, L. (2007). *Climate change 2007: Mitigation of climate change*. https://agris.fao.org/agris-search/search.do?recordID=XF2008415344

Miralinaghi, Correia, G. H. de A., Seilabi, S. E., & Labi, S. (2021). Managing Urban Vehicular Emissions Through the Efficient Design of Electric Charging Station Infrastructure. *Transportation Research Board 100th Annual Meeting*, 21–03592.

Miralinaghi, M., Davatgari, A., Seilabi, S. E., & Labi, S. (2021). Contract Bundling Considerations in Urban Road Project Scheduling. *Computer-Aided Civil and Infrastructure Engineering*.

Miralinaghi, M., Keskin, B. B., Lou, Y., & Roshandeh, A. M. (2016). Capacitated Refueling Station Location Problem with Traffic Deviations Over Multiple Time Periods. *Networks and Spatial Economics*. https://doi.org/10.1007/s11067-016-9320-3

Miralinaghi, M., Lou, Y., Hsu, Y.-T., Shabanpour, R., & Shafahi, Y. (2016). Multiclass fuzzy user equilibrium with endogenous membership functions and risk-taking behaviors. *Journal of Advanced Transportation*, *50*(8), 1716–1734. https://doi.org/10.1002/atr.1425

Miralinaghi, M., & Peeta, S. (2019). Promoting zero-emissions vehicles using robust multi-period tradable credit scheme. *Transportation Research Part D: Transport and Environment*, *75*, 265–285. https://doi.org/10.1016/j.trd.2019.08.012

Miralinaghi, M., Woldemariam, W., Abraham, D. M., Chen, S., Labi, S., & Chen, Z. (2020). Network-level scheduling of road construction projects considering user and business impacts. *Computer-Aided Civil and Infrastructure Engineering*, *35*(7), 650–667. https://doi.org/10.1111/mice.12518

Moon, S., Kim, B. C., Cho, S. Y., Ahn, C. H., & Moon, G. W. (2014). Analysis and design of a wireless power transfer system with an intermediate coil for high efficiency. *IEEE Transactions on Industrial Electronics*, *61*(11), 5861–5870. https://doi.org/10.1109/TIE.2014.2301762

Morris, C. (2015). *Utah State University builds a dynamic wireless charging test track*. http://chargedevs.com/features/utah-state-university-builds-a-dynamic-wireless-charging-test-track/

Mrawira, P. E. D. M., & Amador, L. E. (2009). *"Cross-assets trade-off analysis: Why are we still talking about it?" 88th Annual Meeting of the Transportation Research Board, Washington, DC.*

Nie, Y. (Marco), Ghamami, M., Zockaie, A., & Xiao, F. (2016). Optimization of incentive polices for plug-in electric vehicles. *Transportation Research Part B: Methodological*, *84*, 103–123. https://doi.org/https://doi.org/10.1016/j.trb.2015.12.011

Nie, Y., & Ghamami, M. (2013). *A corridor-centric approach to planning electric vehicle charging infrastructure*. https://doi.org/10.1016/j.trb.2013.08.010

Ono, I., Kita, H., & Kobayashi, S. (2003). *A Real-coded Genetic Algorithm using the Unimodal Normal Distribution Crossover* (pp. 213–237). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-18965-4_8

Overtoom, I., Correia, G., Huang, Y., & Verbraeck, A. (2020). Assessing the impacts of shared autonomous vehicles on congestion and curb use: A traffic simulation study in The Hague, Netherlands. *International Journal of Transportation Science and Technology*, *9*(3), 195–206. https://doi.org/https://doi.org/10.1016/j.ijtst.2020.03.009

Papa, E., & Ferreira, A. (2018). Sustainable Accessibility and the Implementation of Automated Vehicles: Identifying Critical Decisions. *Urban Science*, *2*(1), 5. https://doi.org/10.3390/urbansci2010005

Patidar, V., Labi, S., Sinha, K. C., & Thompson, P. (2007). *Multi-Objective Optimization for Bridge Management Systems*. http://www.trb.org/Publications/Blurbs/159292.aspx

Racherla, K., & Waight, M. (2018). Addressing EMI in Electric Cars with Radio Tuner Architecture [Future Directions]. *IEEE Consumer Electronics Magazine*, *7*(1), 15–124. https://doi.org/10.1109/MCE.2017.2755278

Riba, J.-R., López-Torres, C., Romeral, L., & Garcia, A. (2016). Rare-earth-free propulsion motors for electric vehicles: A technology review. *Renewable and Sustainable Energy Reviews*, *57*, 367–379. https://doi.org/https://doi.org/10.1016/j.rser.2015.12.121

Riemann, R., Wang, D. Z. W., & Busch, F. (2015). Optimal location of wireless charging facilities for electric vehicles: Flow-capturing location model with stochastic user equilibrium. *Transportation Research Part C: Emerging Technologies*, *58*, 1–12. https://doi.org/https://doi.org/10.1016/j.trc.2015.06.022

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

Saeed, T. U., Burris, M. W., Labi, S., & Sinha, K. C. (2020). An empirical discourse on forecasting the use of autonomous vehicles using consumers' preferences. *Technological Forecasting and Social Change*, *158*, 120130. https://doi.org/10.1016/j.techfore.2020.120130

Seilabi, S. E., Tabesh, M. T., Davatgari, A., Miralinaghi, M., & Labi, S. (2020). Promoting Autonomous Vehicles Using Travel Demand and Lane Management Strategies. *Frontiers in Built Environment*, *6*, 560116. https://doi.org/10.3389/fbuil.2020.560116

Shabanpour, R., Golshani, N., Shamshiripour, A., & Mohammadian, A. (Kouros). (2018). Eliciting preferences for adoption of fully automated vehicles using best-worst analysis. *Transportation Research Part C: Emerging Technologies*, *93*, 463–478. https://doi.org/https://doi.org/10.1016/j.trc.2018.06.014

Sinha, K. C., & Labi, S. (2007). *Transportation Decision Making: Principles of Project Evaluation and Programming*. John Wiley & Sons.

Sinha, K., & Labi, S. (2007). *Transportation Decision Making: Principles of Project Evaluation and Programming* (1st ed.). Wiley.

Sinha, Kumares C., Patidar, V., Li, Z., Labi, S., & Thompson, P. D. (2009). Establishing the Weights of Performance Criteria: Case Studies in Transportation Facility Management. *Journal of Transportation Engineering*, *135*(9), 619–631. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000039

Smith, D., Graves, R., Ozpineci, B., Jones, P. T., Lustbader, J., Kelly, K., Walkowicz, K., Birky, A., Payne, G., Sigler, C., & Mosbacher, J. (2019). *Medium-and Heavy-Duty Vehicle Electrification: An Assessment of Technology and Knowledge Gaps*. *December 2019*, 85.

Smith, M., & Castellano, J. (2015). Costs Associated With Non-Residential Electric Vehicle Supply Equipment. *U.S. Department of Energy, Washington DC*, *November*, 1–43.

Tabesh, Miralinaghi, S. M., & Labi, S. (2019). Promoting the Usage of Electric Vehicles Through the Efficient Design of Charging Station Network. *ASCE International Conference on Transportation & Development*.

Talebpour, A., Mahmassani, H. S., & Elfar, A. (2017). Investigating the effects of reserved lanes for autonomous vehicles on congestion and travel time reliability. *Transportation Research Record*, *2622*(1), 1–12. https://doi.org/10.3141/2622-01

Tientrakool, P., Ho, Y. C., & Maxemchuk, N. F. (2011). Highway capacity benefits from using vehicle-to-vehicle communication and sensors for collision avoidance. *IEEE Vehicular Technology Conference*, 0–4. https://doi.org/10.1109/VETECF.2011.6093130

UNFCCC. (2019). *United Nations Climate Change Annual Report 2019*. https://unfccc.int/sites/default/files/resource/unfccc_annual_report_2019.pdf

Ushijima-Mwesigwa, H., Khan, M. Z., Chowdhury, M. A., & Safro, I. (2017). *Optimal Installation for Electric Vehicle Wireless Charging Lanes*. 1–26. http://arxiv.org/abs/1704.01022

Van Brummelen, J., O'Brien, M., Gruyer, D., & Najjaran, H. (2018). Autonomous vehicle perception: The technology of today and tomorrow. *Transportation Research Part C: Emerging Technologies*, *89*, 384–406. https://doi.org/https://doi.org/10.1016/j.trc.2018.02.012

Vaughan, A. (2017). *All Volvo Cars to Be Electric or Hybrid from 2019. The Guardian.*

Wang, I.-L., Wang, Y., & Lin, P.-C. (2016). Optimal recharging strategies for electric vehicle fleets with duration constraints. *Transportation Research Part C: Emerging Technologies*, *69*, 242–254. https://doi.org/10.1016/J.TRC.2016.06.010

Wang, Y. W., & Wang, C. R. (2010). Locating passenger vehicle refueling stations. *Transportation Research Part E: Logistics and Transportation Review*, *46*(5), 791–801. https://doi.org/10.1016/j.tre.2009.12.001

WARDROP, J. G. (1952). ROAD PAPER. SOME THEORETICAL ASPECTS OF ROAD TRAFFIC RESEARCH. *Proceedings of the Institution of Civil Engineers*, *1*(3), 325–362. https://doi.org/10.1680/ipeds.1952.11259

Woo, S., Bae, S., & Moura, S. J. (2021). Pareto optimality in cost and service quality for an Electric Vehicle charging facility. *Applied Energy*, *290*. https://doi.org/10.1016/j.apenergy.2021.116779

Wu, F., & Sioshansi, R. (2017). A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows. *Transportation Research Part D: Transport and Environment*, *53*, 354–376. https://doi.org/https://doi.org/10.1016/j.trd.2017.04.035

Xu, M., Yang, H., & Wang, S. (2020). Mitigate the range anxiety: Siting battery charging stations for electric vehicle drivers. *Transportation Research Part C: Emerging Technologies*, *114*, 164–188. https://doi.org/https://doi.org/10.1016/j.trc.2020.02.001

Yadav, S. L., & Sohal, A. (2017). Comparative Study of Different Selection Techniques in Genetic Algorithm. In *International Journal of Engineering, Science and Mathematics* (Vol. 6).

Yang, J., Guo, F., & Zhang, M. (2017). Optimal planning of swapping/charging station network with customer satisfaction. *Transportation Research Part E: Logistics and Transportation Review*, *103*, 174–197. https://doi.org/10.1016/J.TRE.2017.04.012

Zakaria, H., Hamid, M., Abdellatif, E. M., & Imane, A. (2019). Recent Advancements and Developments for Electric Vehicle Technology. *2019 International Conference of Computer Science and Renewable Energies (ICCSRE)*, 1–6. https://doi.org/10.1109/ICCSRE.2019.8807726

Zheng, H., He, X., Li, Y., & Peeta, S. (2017). Traffic Equilibrium and Charging Facility Locations for Electric Vehicles. *Networks and Spatial Economics*, *17*(2), 435–457. https://doi.org/10.1007/s11067-016-9332-z

Zhu, Z.-H., Gao, Z.-Y., Zheng, J.-F., & Du, H.-M. (2016). Charging station location problem of plug-in electric vehicles. *Journal of Transport Geography*, *52*, 11–22. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2016.02.002

Zhuge, C., & Wang, C. (2021). Integrated modelling of autonomous electric vehicle diffusion: From review to conceptual design. *Transportation Research Part D: Transport and Environment*, *91*, 102679. https://doi.org/10.1016/j.trd.2020.102679