Enabling Large-Scale Transportation Electrification for Shared and Connected Mobility Systems

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ENABLING LARGE-SCALE TRANSPORTATION ELECTRIFICATION FOR SHARED AND CONNECTED MOBILITY SYSTEMS

by

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Major Professor: Zhaomiao Guo
Owing to advancements in technology, substantial investments within the automotive industry, and the formulation of supportive state policies, the future landscape of the transportation sector is poised to witness a shift from traditional internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). While EVs have made inroads in the market, they still face significant hurdles in the form of range anxiety and prolonged charging durations, inhibiting their widespread adoption. To tackle these challenges, a comprehensive approach to smart transportation electrification is proposed, emphasizing the pivotal roles of infrastructure development, particularly in the allocation of charging stations, and strategic operational decisions, including charging and platoon scheduling. This dissertation is structured around four essential components. The initial stage entails grasping the intricacies of charging demand, recognized as the foundational step before embarking on any transportation electrification initiative. Subsequently, the allocation of charging stations is addressed, with a specific focus on ride-sourcing vehicles, distinct from private EVs due to issues such as relocation time, waiting time, and dynamic pricing that affects spatiotemporal value of time (VOT) costs. This approach, which considers VOT costs, is essential in avoiding biased results in the planning of charging infrastructure for electrified ride-sourcing services. The third chapter centers on the optimization of charging and platoon scheduling, particularly within the context of long-haul freight vehicles. The objective here is to harness the flexibility of charging schedules to facilitate vehicle platooning, thereby reducing the demand for charging, and, consequently, energy consumption. This chapter involves the development of a mixed-integer programming model and explores various techniques, such as hyperparameter tuning and hybrid meta-heuristic methods, to optimize the model for large-scale applications. Lastly, the fourth chapter takes on the challenge of addressing uncertainty in scheduling problems. This is achieved by formulating a two-stage stochastic model and applying it within a hypothetical numerical example, providing a framework
for optimizing charging station (CS) planning while accounting for uncertain operational parameters.
To my family
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CHAPTER 1: INTRODUCTION

Background

The transportation sector is responsible for 65% of global oil energy demand and 24% of global carbon dioxide emission from fuel consumption [55]. The transport energy demand is projected to double by 2050 [89]. Instead of using traditional fuel energy, electric energy in vehicles can significantly reduce global carbon dioxide emissions and overall fuel energy demand. Factors including tax incentives, manufacturer rebates [62], rapid expansion of charging networks [23], policies to reduce charging costs [107], technological advancements, automotive-industry investments and state policies, etc. have contributed to the increasing adoption of EVs.

Based on 2021 data, the global market share of electric vehicles (EVs) is 8.57%[84]. Bloomberg’s New Energy Finance projects that 55% of new sales of automobiles worldwide will be EVs by 2040. Besides private car users, transportation network companies (TNC) also show interest in EVs. For example, Uber and Lyft announced plans to increase the share of EVs in their vehicle fleet [58, 73].

Recently, several auto manufacturers, such as Daimler, Mack, Tesla, Nikola, Volvo, Navistar, Rivian, and DAF, have announced plans to launch electric freight vehicles (EFVs) in the market [51]. Most of the major delivery companies are also starting to expand their electric fleet. For example, UPS has initiated a purchase of 10,000 electric delivery vehicles, while Amazon has committed to acquiring 100,000 EFVs through the emerging company Rivian [65]. Additionally, in February 2021, the United States Postal Service granted a contract for the production and deployment of 50,000 to 165,000 EFVs over 10 years [98].
Challenges and Research Gaps

While there is a noticeable increase in the market share of EVs, the challenges of range anxiety and extended charging times persist as significant hurdles, hindering widespread adoption of EVs in the current transportation system [44, 102]. In the context of shared mobility, ride-sourcing vehicles experience higher vehicle miles traveled (VMT) with short-duration dwelling time, and less charging opportunities [9], which could potentially contribute to a substantial rise in range anxiety. In terms of connected vehicles, long-haul platooned EFVs experience charging and platooning opportunity crises due to sparse DC fast charging (DCFC) stations. In the real world, there are many uncertainties in operations such as vehicle speed, trip demand, platoon’s energy-saving percentage, etc. The uncertainty of such attributes is crucial for long-term charging infrastructure planning. Such challenges necessitate extensive study on charging demand, CS planning, and scheduling of charging and platooning to have smart and resilient transportation electrification.

Understanding the charging demand is the first and most important stage before any scheme is taken for transportation electrification. To assess charging demand, it is essential to have detailed daily trip information (e.g., trip chain) for each vehicle. Obtaining trip chain data for TN drivers is challenging due to privacy concerns.

Given the charging demand information is available, efficient planning for the deployment of CSs and plugs (i.e., EVSE) is required. To mitigate range anxiety among EV users, researchers have extensively explored Charging Station Allocation Problems (CSAPs), considering node-based, flow-based, or path-based charging demand models. Nevertheless, traditional CSAPs may not be well-suited for ride-sourcing systems. This is because drivers in ride-sourcing platforms may exhibit varying Value of Time (VOT) at different locations and times, influenced by dynamic pricing mechanisms[105]. Therefore, conducting a study on CSAP that takes into account spatio-temporal VOT is imperative for supporting the integration of EVs into ride-sourcing systems.
The benefit of physical deployment of CSs can be augmented by operational scheduling for EFVs. Scheduling for platoon and charging can minimize energy consumption. Among EFVs, long-haul heavy-duty EFVs are used for transporting freight from the retailer’s warehouse/distribution center to its retail store. A good number of the EFV studies are found for last-mile logistics which are used for first-mile pickup and last-mile delivery and require less charging demand. First and Last-mile EFVs usually charge at the depot, unlike long-haul middle-mile EFVs. The methodologies of first and last-mile EFVs charging-scheduling studies may not be directly transferable to long-haul middle-mile EFVs because of higher charging demand, en-route charging demand, and less CS availability on the road network[17]. As the long-haul EFVs are heavy-duty trucks they are good candidates to exploit the benefit of platooning. However, the study on co-optimizing charging and platooning schedules for heavy-duty long-haul EFVs was not studied in previous literature.

The uncertainty of scheduling problem is common in real-world cases. The long-term planning for EVSEs at CSs considering the uncertainties is overlooked in previous studies.

Dissertation Objective

This dissertation addresses the research gaps in infrastructure and operational planning of large-scale transportation electrification systems for connected and shared mobility. It focuses on the following specific objectives:

- Propose an optimization-based methodology to generate trip-chain information where trip-chain information is unavailable and estimate charging demand using a micro-simulation technique.

- Develop an optimization model to plan charging station allocation considering spatio-temporal dynamic VOT.
• Develop an optimization model of charging and platooning scheduling for heavy-duty long-haul electric freight vehicles and provide solution techniques for solving large-scale model instances.

• Develop a two-stage stochastic optimization model to optimize the EVSE allocation while considering uncertainty in the scheduling problem.

Dissertation Contribution

This dissertation contributes to the transportation research field in the following ways:

• If the trip chain of ride-sourcing drivers is unavailable, the trip-chain emulation method proposed in this dissertation can resolve the issue.

• Better charging station planning considering the spatial-temporal value of time is achievable for shared mobility within any study area.

• The co-optimized scheduling model of charging and platooning will minimize energy consumption for long-haul electric freight vehicles in the road network.

• Uncertainties of operations can be addressed for long-term EVSE planning.

Structure of The Dissertation

In Chapter 2, an extensive examination of the literature is undertaken in alignment with the four primary studies in this dissertation. Chapter 3 outlines the fundamental aspects of the central methodology employed in each of these studies. The intricate methodologies are expounded upon
in dedicated chapters specific to each study. Alongside the methodologies, the chapters corresponding to the four studies present problem statements, assumptions, results based on case studies or hypothetical examples, conclusions, limitations, and future research direction. The concluding chapter provides an overall summary, limitations, and future research direction. Notably, the dissertation draws upon three research papers published in reputable journals, including references [5, 2, 3].
CHAPTER 2: LITERATURE REVIEW

We start with literature review on charging demand followed by CS allocation planning and finally, charging scheduling for connected and shared mobility.

Review on Charging Demand Study

Previous Studies on Charging Demand

The fear of insufficient driving range, commonly referred to as range anxiety, is frequently identified as a primary impediment to the widespread adoption of EVs [45]. Various studies delved into mitigating the challenge of range anxiety, exploring diverse aspects. For instance, some research endeavors concentrate on gaining a deeper understanding of EV charging behaviors and the associated charging demand. Utilizing demand-side surveys [34] and supply-side charging records [53], insights are gathered to comprehend the patterns of EV charging in terms of the timing, location, and methods employed by EV owners. The study by [86] explored the EV charging load dynamics over time within a distribution network. Meanwhile, [12] developed a model for locational EV charging demand, specifically focusing on a DC fast charging station near a highway corridor, without incorporating detailed travel or charging behaviors. Investigations by [102] and [77] delved into charging behaviors and potential infrastructure requirements in Columbus, Ohio, and Chicago, Illinois, respectively.

A substantial body of literature has addressed optimal charging infrastructure planning, utilizing node-based [61], flow-based [50, 63], or activity-based [59, 93] charging demand models. These planning approaches are applied in either centralized [35, 70] or competitive markets [44], catering to single-stage [68] or multi-stage [69] settings. Other studies explore the integration of charging
activities with power system operation to maximize the value of EVs [46, 43, 13]. Notably, all these studies primarily focus on EVs for daily household travel rather than for ride-sourcing services.

**Previous Studies on Ride-sourcing EVs**

Recently there has been a growing research focus on exploring transportation electrification in ride-sourcing services [94]. In addition to potential environmental advantages [39, 57], the introduction of EVs introduces complexities into ride-sourcing operations due to their generally limited battery range compared to conventional vehicles and significantly longer charging times. [106] developed an optimal routing algorithm for EV pick-up and charging in ride-sourcing services, and [40] employed deep reinforcement learning to formulate EV charging strategies for TNC drivers. While these studies have made noteworthy advancements in addressing the charging strategies of EVs in the ride-sourcing market, they did not specifically tackle the distribution of charging load and the charging infrastructure needs at a systemic level. In specific cases like Austin, Texas, trip chain information is accessible. [100] analyzed real trip chain data from the RideAustin database and found that new generation EVs with 200 miles of range would be able to fulfill 90% of full-time drivers’ shifts on a single charge. These analysis results support the study by [16], who found that electrified TNCs have enough time to charge sufficiently while satisfying demand and potentially cutting costs. The study conducted by [101] employed data from RideAustin to analyze and comprehend the charging infrastructure requirements through the application of demand clustering techniques. A general approach is needed to verify the charging demand of electrified TNC fleets even when real trip chain data is unavailable for ride-sourcing services.
To overcome data limitations within the ride-sourcing sector, previous studies such as [102] and [38] utilized GPS data extracted from installed cellular applications to capture vehicle trip information. However, these datasets lacked the ability to differentiate between ride-sourcing and non-ride-sourcing trips. In the case of [102], driver-rider matching was heuristic, aiming to emulate ride-sourcing trip chain information by minimizing individual pick-up times, which may not accurately reflect current practices where TNCs prioritize minimizing the total system waiting time.

In another instance, [40] utilized available NYC taxicab data as a proxy for the ride-sourcing context, lacking complete trip chain information except for pick-up zones and hours. To emulate trip chain information, probabilistic models were used to randomly generate requested trips based on the time of day and the EV’s current location. Similarly, [16] estimated trip chain information for ride-sourcing by sampling from the available trip-level data of NYC taxis, matching hourly times and pick-up areas without explicit consideration of the driver-rider matching mechanism.

In summary, when faced with data unavailability, previous studies emulated trip chain information in a simplified manner, overlooking the influence of the driver-rider matching mechanism and drivers’ working hours—factors that significantly impact the daily driving patterns of ride-sourcing vehicles. Addressing this research gap forms the primary focus of our charging demand study.
Review on Charging Station Allocation Study

Previous Studies on Charging Station Allocation

Extensive literature has looked into the optimal strategies of charging network deployment considering various charging demand models, which can be broadly categorized into three main categories: node-based, flow-based, and trajectory-based approaches. The node-based CSAP studies (e.g., [14, 24, 11, 27, 33]) are typically based on classic node-based facility location problems (e.g., p-median, p-center, set covering problems). These studies mainly focus on origin/destination charging and may not be effective in modeling en-route charging behavior [61]. To address this limitation, flow-based approaches have been introduced, relying on the Flow Capturing Location Model (FCLM) as proposed by [50]. The FCLM aims to optimize the allocation of a fixed number of charging stations to maximize the one-time flow-based exposure of EVs to charging facilities. A noteworthy pioneer in flow-based CSAP studies is the Flow Refueling Location Model (FRLM), designed to consider the driving range of alternative fuel vehicles [63]. Other studies adopting flow-based CSAP methodologies include [10, 22, 41, 60, 42]. However, it is worth noting that charging decisions in these models may not be made at the individual trip level. Models based on vehicle trajectories were introduced to account for the daily travel paths of EVs [47, 59, 93, 71]. In trajectory-based models, the determination of charging locations is contingent upon factors such as the remaining distance to be covered, the current SOC, and the availability of charging stations at specific locations. Furthermore, various studies within this framework have explored diverse objectives, including the maximization of electric-vehicle miles traveled (electric-VMT) [93] and the minimization of total waiting time at charging stations [97].

For a detailed review of CSAP, one can refer to [31, 83]. A majority of existing CSAP studies concentrate on vehicles intended for private travel rather than those involved in ride-sourcing services.
This study seeks to address this gap by aiming to strategically deploy both charging stations and plugs to meet the charging requirements of electrified ride-sourcing services. The optimization objective is to minimize total system costs through a trajectory-based approach.

**Charging Station Allocation for Ride-sourcing Vehicles**

In contrast to private travel, the relocation time to charging stations and the waiting time due to queuing, pose challenges for ride-sourcing drivers in picking up new riders. These challenges may incur spatio-temporally varying opportunity costs due to dynamic pricing set by TNCs. Research efforts have been directed towards minimizing waiting time from queuing for electric taxi and dial-a-ride services within the charging infrastructure planning process [103, 90, 104, 75].

Certain studies consider charging only when vehicles are idle or at destinations during dwell time [103], while others contemplate en-route charging [90]. Combining either en-route charging or destination charging with queuing time, [104] proposed a model to maximize rider pick-up demand and minimize travel time to charging stations and waiting time at those charging stations. In addition to minimizing queuing time, there are also studies focused on reducing idle time, as exemplified by [75]. Notably, these studies did not incorporate the daily travel trajectories of ride-sourcing vehicles or the spatio-temporally varying VOT for ride-sourcing drivers.

More recently, few studies have considered the optimal relocation and scheduling of ride-sourcing EVs for charging purposes. For example, [56] developed a mixed-integer programming model to decide when, where, and how much each taxi should charge in real-time. [52] analyzed the feasibility of ride-sourcing EVs from taxi travel patterns in New York. [16] developed an agent-based model considering vehicles’ relocation for charging. [74] introduced and integrated an online vehicle-charging assignment model into the dynamic ridesharing service for electric vehicles (EVs) while addressing the fast charging location problem. The existing studies fail to address charging
infrastructure planning comprehensively and do not account for any costs associated with Values of Time (VOT). [6] addresses charging station placements for ride-sourcing vehicles to minimize the total cost, which includes costs associated with empty time traveled to the nearest charging stations and charging station installations. This study explicitly distinguishes between on-street and off-street EV charging stations. However, it does not consider the temporal dynamics of the ride-sourcing system in the location-allocation problem.

On the other hand, [97] formulates a spatial-temporal demand coverage model to locate charging stations for electric taxi services, aiming to minimize the electric taxi service level and the total waiting time for charging. Nevertheless, the optimization model in [97] is not explicitly stated, and the solution is obtained heuristically using a genetic algorithm, which may not guarantee a global optimum. Additionally, spatio-temporally varying VOT is not taken into account in [97] within the context of taxi services.

Review on Charging and Platoon Scheduling Study

Previous Studies for Electric Freight Vehicles

The existing literature has explored the consequences and effects of EFVs adoption within transportation systems. For example, [82, 54] studied the potential benefits of introducing EFVs in the transportation sector with consideration of environmental emissions. [99] studied the economic benefits of EFVs in the road transportation sector. [81, 92] investigated the necessity of battery improvement and the competitiveness of EFVs with conventional diesel-fueled trucks. The related transportation policies was also studied to better promote EFV adoption [95].

Compared with studies on first-mile (i.e., shipments from manufacturer’s factory to warehouses) and last-mile (i.e., shipments from retail stores to customer’s home) freight, studies for middle-
mile (i.e., shipments from warehouses to retail stores) EFVs are still limited. Last-mile logistics has been extensively studied for EFVs with an emphasis on vehicle routing problems [15, 18, 8]. The important factors investigated in these studies include energy consumption (e.g., deterministic or stochastic [20]), battery charging behavior (e.g., fully charged [49, 7] or partially charged at charging stations (CSs) [32]), and CS location (e.g., only at depots [85] or en-route charging [20]). The charging-scheduling research typically focuses on single EFV charging strategies [20] and/or assumed exogenous charging behaviors such as full charging of the battery once plugged in at CSs [49, 7]. However, these studies did not explore the long-haul middle-mile delivery nor platooning possibility was considered.

Middle-mile freight systems have distinct operational characteristics compared with first/last-mile delivery, including energy consumption, charging station availability, charging behavior, and delivery-related constraints. Therefore, the charging scheduling strategies for the first/last mile can not be generally applied and platooning is not applicable. For example, first and last-mile EFVs exhibit relatively lower charging requirements per trip, leading to a higher likelihood to only charge the EFVs at depots [28]. Furthermore, in contrast to the abundance of CSs in city areas, middle-mile freight vehicles often encounter limited availability of CSs, with charging stations being sparsely distributed [17]. Apart from studies on EFVs, the extensive passenger EV-based charging scheduling research is not worthy of straightforward implementation due to the unique charging behaviors of passenger EVs. For instance, factors like nighttime charging at home [78] and destination charging at parking spots [25] create unique challenges specific to EFVs. In addition, while passenger EVs often do not adhere to strict travel schedules, middle-mile EFVs must operate within specific time windows for delivery purposes.

Studies have been conducted to understand the energy-saving benefit of platooned vehicles for different arrangements among the vehicles in a platoon [76, 30, 96, 1]. [66] proposed a mathematical programming model for platoon scheduling that decides the optimal coordination of platooned
EFVs. The goal was to minimize energy consumption and carbon footprint by platooned EFVs. However, the authors did not consider platooning coordination at a network level. [80] proposed an integer programming model for platooned heavy-duty vehicles in the road network connecting twenty German cities. That model fixed the departure time of trucks at the beginning of the day and the delivery time before the due time. [79] studied the platooning schedule adjusting the truck’s speed on the US national highway network. Nonetheless, these studies either focused on traditional fossil-fueled trucks or did not explore the fundamental characteristics of EFVs, such as the dynamics of battery state of charge (SOC) and the schedule of en-route charging.

Previous Studies Combining Platoon and Charging

Although recent studies are found to consider platooned vehicles for charging scheduling, they have assumed the availability of wireless CS that can not reflect plug-in charging and/or long-haul EFVs. For instance, [72] proposed a model to assign charging-needy vehicles to mobile-charger vehicles for platoon-based charging. In another study, [108] planned wireless charging during the wait time at signalized intersections. In contrast, [3, 91] independently proposed a model co-optimizing the schedules of charging and platooning for long-haul EFVs with different objective functions and operating constraints (e.g., [91] optimized the total cost of energy consumption considering platoon position using meta-heuristic approaches whereas [3] minimized the total cost of delivery delay, hub (i.e., depot) charging, and en-route charging considering the charging station capacity and solved the problem by CPLEX). However, these studies focused on a single route and single OD pair (i.e., corridor), which may limit the platoon and charging flexibility compared with the case when multiple origin-destination (OD) pairs over the transportation network are considered. A scheduling decision of charging and platooning at a network level can reflect the real-world interaction among the EFVs serving different OD pairs. In addition, including EFVs from different ODs over the network allows for more platooning opportunities, which leads to more significant
energy and environmental benefits.

In summary, most of the previous studies focus on only one of the technologies (charging scheduling or platoon coordination) for last-mile freight delivery. Although recently, [3] and [91] have proposed optimization models for EFV charging and platooning coordination, only a single route has been considered and the models cannot be directly generalized to the charging and platooning scheduling problem at a network level with multiple OD pairs. To mitigate this critical research gap, this study aims to jointly optimize the decisions for the schedule of charging and platooning of EFVs over a general transportation network.
CHAPTER 3: METHODOLOGY

Agent-based Modeling

Agent-based modeling (ABM) is one kind of micro-simulation approach. In ABM, the behavior of individual agents and the interaction among themselves are modeled. The agent-based model satisfies the desire to get deeper insights into a system that traditional modeling approaches do not capture well. Agent-based simulation helps to understand and manage the complexity of today’s business and social systems including transportation systems. There is extensive usage of agent-based modeling to understand supply chain management (e.g., optimization), epidemiology (e.g., public health intervention against the spreading of viruses), transportation systems (e.g., testing algorithms for self-driving cars, minimizing traffic congestion), etc.

Today’s companies and governmental organizations have accumulated large amounts of data in their databases. Agent-based simulation modeling is a powerful approach to put that data to work. An agent-based simulation model featuring individuals can use properties and behaviors taken directly from these databases. The results deliver insightful inferences about the system by comparing scenarios.

Structure of an Agent-based Model

A typical agent-based model has three elements

- Set of Agents: Each agent has their attributes and behaviors. For example, in a transportation system, an agent ”electric vehicle (EV)” has its battery configuration. In addition, the electric vehicle has its behavior either as a private vehicle or a ride-sourcing vehicle.
• Interaction among agents: Each agent interacts with system infrastructures using methods and develops relationships. For example, an EV can go for charging when the state of charge (SOC) is less than 20%. When charging is done, the vehicle can roam on the road or go to the parking garage based on its behavior. If an EV is for ride-sourcing purposes, the EV will roam on the road until it gets a passenger pick-up request. If the EV is a private vehicle, it may go to home parking.

• Agents’ environment: Agents interact with their environment in addition to other agents. For the ride-sourcing system, the environment includes drivers, passengers, ride-sourcing managers, fueling stations, etc.
Bipartite Matching Algorithm

Bipartite matching algorithms are algorithms used to solve bipartite graph matching problems in graph theory. A bipartite graph is a graph whose vertices can be partitioned into two disjoint sets, and all edges connect vertices from different sets. The goal of bipartite matching is to pair the vertices from one set with vertices from the other set in a way that maximizes or minimizes a certain objective function. For example, to match rider and driver on a ride-sourcing app.

A bipartite graph $G = (\mathcal{V}, \mathcal{E})$ is a graph in which the vertex set $\mathcal{V}$ can be divided into two disjoint subsets $\mathcal{X}$ and $\mathcal{Y}$ such that every edge $e \in \mathcal{E}$ has one endpoint in $\mathcal{X}$ and the other endpoint in $\mathcal{Y}$. A matching $M$ is a subset of edges such that each node in $\mathcal{V}$ appears in at most one edge in $M$. A maximum matching is a matching with the largest possible number of edges and it is globally optimal.
Different bipartite matching algorithms are being used for different purposes. For example, the Ford-Fulkerson algorithm is used for the maximum flow problem, Hungarian matching algorithm for rider-driver matching.

**Hungarian Algorithm**

The Hungarian matching algorithm performs a stable and maximum/minimum weight matching in a bipartite graph. For a maximum weight matching problem between two sets of vertices (i.e., \( x_i \) and \( y_j \)) can be represented by a bipartite graph with cost, \( w(i, j) \) is assigned to edge \( x_i y_j \) of the graph. We seek a perfect matching \( M \) to maximize the total weight \( w(M) \).

The dual of this maximum weighted bipartite matching problem is a minimum weighted cover problem to find a cover of minimum cost. A weighted cover is a choice of label \( u_i \) and \( v_j \) so that label \( u_i + v_j \geq w_{i,j} \forall i, j \). Here, \( u_i \) and \( v_j \) denote the weights for two vertices \( x_i \) and \( y_j \), respectively. The cost of cover \( c(u, v) \) is \( \sum_i u_i + \sum_j v_j \).

In the Hungarian algorithm, the input is a matrix of weights on the edges of the graph with bipartition \( X \) and \( Y \). The idea of the algorithm is to iteratively adjust the cover \((u, v)\) until the equality subgraph \( G_{u,v} \) has a perfect matching as described in Algorithm 1. The equality subgraph \( G_{u,v} \) for a weighted cover \((u, v)\) is the spanning subgraph of the graph whose edges are the pairs \( x_i y_j \) such that \( u_i + v_j = w_{i,j} \).
Algorithm 1 Hungarian algorithm

**Initialization:** Let, \((u, v)\) be a cover, such as \(u_i = max(w_{i,1}, w_{i,2}, ..., w_{i,j})\) and \(v_j = 0\)

**Iteration:**
Find a maximum matching \(M\) in \(G_{u,v}\)
- if \(M\) is a perfect matching then
  - Stop and report \(M\) as a maximum weighting matching
- else if \(M\) is not a perfect matching then
  - Let \(Q\) be a vertex cover of size for \(|M|\) in \(G_{u,v}\). \(|M|\) denotes the number of edges in matching
  - Let excess \((\varepsilon) = min(u_i + v_j - w_{i,j}) : x_i \in X \setminus R, y_j \in Y \setminus T\)
  - Change the cover to \((u', v')\) as follows
    - if \(x_i \in X \setminus R\) then
      - \(u_i' = u_i - \varepsilon\)
    - else if \(y_j \in T\) then
      - \(v_j' = v_j + \varepsilon\)
    - else if \(x_i \in R\) and \(y_j \in Y \setminus T\) then
      - \(u_i' = u_i\) and \(v_j' = v_j\)
  - end if
- end if
- Form the new equality subgraph and repeat

---

Mixed Integer Programming

A mixed integer programming (MIP) model is a special type of integer programming (IP) model whereas an IP model is a special type of linear programming (LP) model. LP is an operations research technique used to determine the best outcome in a mathematical model where the objective and the constraints are expressed as linear equations. IP is an LP with an additional allowance for some or all variables to be integer values. If some variables are integer and the remaining variables are non-integer, then the IP model becomes an MIP model.
An MIP model can be formulated of the form:

\[
\begin{align*}
\text{minimize} & \quad \sum_{j \in J} c_j x_j \\
\text{subject to} & \quad \mathcal{A} x \geq b \\
& \quad l_j \leq x_j \leq u_j \quad \forall j \in J \\
& \quad \text{some} \ x_j \text{ are integer and some are non-integer}
\end{align*}
\]  

(3.1)

The goal of this MIP model is to minimize the objective function defined as 3.1a. The MIP model includes constraints. Here, constraint 3.1b represents the non-equality constraint and 3.1c represents the boundary values for each variable. The variables are a mixture of integer and non-integer type variables defined in constraint 3.1d. If all variables are integer, the model becomes an IP model. In an IP model, if all integers are binary then the model is called binary integer programming model (BIP).

Two-stage Stochastic Programming with Fixed Recourse

In stochastic programming, some parameters may be considered uncertain the probabilistic statistics of which are known. Recourse actions can be taken after the uncertainty is disclosed. In other words, the vector of uncertain parameters is only known after the incident. The decision set is divided into two portions. The first portion of decisions (first stage decision) is taken before the experiment, whereas the second portion of decisions (second stage decision) is taken after the experiment.

The classical two-stage stochastic linear program with fixed recourse is originated by [29] and
formulated as 3.2a-3.2c.

\[
\text{minimize } z = c^T x + E_\xi [\text{minimize } q(\omega)^T y(\omega)] \\
\text{subject to }
\begin{align*}
Ax &= b \\
T(\omega)x + W y(\omega) &= h(\omega) \\
x &\geq 0 \\
y(\omega) &\geq 0
\end{align*}
\]

(3.2a-3.2e)

First-stage decisions are represented by the vector \( x \), while second-stage decisions are represented by the vector \( y(\omega) \). In the second stage, a number of scenarios \( \omega \in \Omega \). For a given scenario \( \omega \), the second-stage problem data \( q(\omega) \), \( h(\omega) \) and \( T(\omega) \) are known.

The first segment of the objective function 3.2a is deterministic. The second segment is the expectation of the second-stage objective \( q(\omega)^T y(\omega) \) considers all scenarios of \( \Omega \). The deterministic equivalent of the stochastic model with fixed recourse can be formulated as a whole in 3.3a-3.3c where \( Q(x) = E_\xi Q(x, \xi(\omega)) \).

\[
\text{minimize } z = c^T x + Q(x) \\
\text{subject to }
\begin{align*}
Ax &= b \\
x &\geq 0
\end{align*}
\]

(3.3a-3.3c)

For a particular scenario, the second stage is formulated as 3.4a-3.4d.
\[ Q(x, \xi(w)) = \minimize_y q(\omega)^T y(\omega) \] 

subject to

\[ T(\omega)x + W y(\omega) = h(\omega) \]  

\[ x \geq 0 \]  

\[ y(\omega) \geq 0 \]
CHAPTER 4: CHARGING DEMAND ESTIMATION

Problem Statement

Although OD trip data from the demand side are available, driver trip-chain information is not generally available, which prevents us from accurately assessing the spatial-temporal charging need of electrified TNC services. Therefore, the problem of interest in this chapter is to propose a novel methodology, integrating unsupervised learning and combinatorial optimization to emulate the vehicle trip chains. In addition, this chapter conducts an agent-based simulation to investigate the potential charging demand and charging infrastructure needs for electrified ride-sourcing services.

Assumptions

In this study, the following assumptions were considered:

- Battery energy consumption was proportional to the traveled distance and vehicle miles per gallon equivalent (MPGe). Other factors, such as real-time congestion, terrain, and weather were not considered.

- Each TNC driver could get access to level 2 chargers at home.

- Ride-sourcing fleet had the same model distribution as the current BEV registration.

- The distribution of working hours in Chicago was the same as the working hours in Austin.

- Among the utilities for choosing a charging station, coefficients for locational attractiveness and charging prices were assumed zero. The reason for this assumption is due to the lack of data on location-based charging prices and drivers’ charging behavior.
• Drivers looked forward to the next three trips and maintained a minimum of 20% SOC to avoid accidentally running out of charge.

The assumed distribution of working hours for Chicago TNC drivers was the same as that of RideAustin TNC drivers with a mean of 3 hours. Given the city’s characteristics, Chicago TNC drivers are expected to drive more working hours. Consequently, the sensitivity analysis in this chapter encompasses working hours ranging from 3 to 8 hours to understand the impact of longer working hours in busy cities including Chicago. The assumption of the driver’s planning ahead of the next three trips is justified by simulation results of daily VMT per trip. The remaining assumptions point towards potential avenues for future research.

Methodology

Agent-based Transportation Energy Analysis Model (ATEAM)

ATEAM is built on an open-source agent-based modeling framework, Repast Simphony which was developed by Argonne National Laboratory.

Structure of ATEAM

In ATEAM, consumers (i.e., passengers/riders), vehicles/drivers, and managers are considered agents. Vehicles and consumers are the movable agents. Roads, fueling stations, tracts, etc. are immovable components of the model environment. Agents and the environment interact and build relationships through (java) methods.

As ATEAM is a developed object-oriented framework, the sets of agents and environments are
defined in class. The interaction between agent and environment objects are performed through methods. The overall operation starts from a class named “Background Engine”

Figure 4.1: Agent and Environment in ATEAM

Figure 4.1 shows the basic elements of ATEAM. The attributes of agents are retrieved from the database in an XML file. The vehicle is one of the important agents that moves during the schedule. Environment agent includes roads, tracts, charging stations, and households. The geometric attributes of the environment are retrieved from Shapefiles.

Consumer-driver Interaction

In ATEAM, consumers send trip requests to the public manager. The manager forwards the trip-request to vehicles and an underlying function does the job of matching. Hungarian matching algorithm was used to match vehicle-consumer (i.e., driver-passenger). Here the TNC authority aliases with the public manager.
State of Vehicle Agent

A vehicle could be in one of six statuses: parking, home parking, driving, charging, home charging, and cruising. In general vehicle is either in ”moving” or ”still” condition. Moving includes driving (re-routing, pick-up, ride) and cruising. On the other hand, still includes parking (home parking and public parking) and charging.

Home parking represents that a vehicle is parked at home when there is no schedule of task. Assuming the vehicle is sufficiently charged, the home-parking state switched to cruising. Cruising means the ride-sourcing vehicle will roam on the road until any pick-up request arrives from the public manager. If the pick-up departure time is due, the vehicle will go to the pick-up passenger, hence, the cruising state switches to the driving state. After delivering the passenger to the destination, the driving state switches to the cruising state.

After vehicle’s arrival at the destination, if the vehicle has a gap time until the next trip and the gap
duration is larger than the minimum charging duration and charging is required then the vehicle will search for the nearest charging station and charge. If a charging station is not available, the vehicle will switch to a parking state. If the vehicle does not have sufficient charge to complete the ride for the passenger, then it will go to the charging station and switch to charging. After any important decision, the ride information is updated and the manager is aware of this.

Trajectory and Result Output in GUI

![Figure 4.3: Trajectory in GUI](image)

Driver-rider Matching

We utilized fundamental driver-rider matching technologies relying on minimum-weight bipartite matching. By generating a synthetic driver population specific to the study area, we iteratively
paired drivers with trips at regular intervals, such as every 15 minutes. The matching procedure is outlined in Figure 4.4.

Starting from $t = 1$ (e.g., 3 a.m.), we iteratively matched total available drivers in the system with all the trips at each time period $t$ using the Hungarian algorithm [64]. The set of available drivers at time $t$ and the set of trips starting at time $t$ are denoted as $\mathbb{D}_t$ and $\mathbb{I}_t$, respectively. Since every trip needs one and only one driver $d \in \mathbb{D}_t$ to pick up, $|\mathbb{D}_t| \geq |\mathbb{I}_t| \ \forall t$. If $|\mathbb{D}_t| < |\mathbb{I}_t|$ at time $t$, new drivers with randomly sampled work schedules would be added. The work schedules for driver $d$ is denoted as $\mathbb{T}_d$. A driver $d$ is labeled as available, and is therefore included in the set of available drivers $\mathbb{D}_t$, if and only if (i) $t \in \mathbb{T}_d$; and (ii) $t \geq t_{i-1,d}^e$, where $t_{i-1,d}^e$ is the ending time of the last

Figure 4.4: Iterative Matching Procedure
trip of driver $d$. Condition (i) means that driver $d$ is online at time step $t$; condition (ii) means that driver $d$ has finished his/her last trip at time $t$. For a newly added driver, the second condition is always satisfied since no previous trip has been assigned and $t^e_{i-1,d} = 0$.

The start/end time and corresponding location for a trip $i \in I$ are denoted as $t^s_i/t^e_i$ and $l^s_i/l^e_i$, respectively, which are typically available from demand-side TNC trip data or household travel surveys. The location of driver $d$ at time $t$, denoted as $l_{t,d}$, is determined by the driver’s last trip destinations, denoted as $l^e_{i-1,d}$. For a newly added driver, its initial location is randomly generated within the study area.

Based on the available driver set ($D_t$) and trip set ($I_t$) at time $t$, we can create a complete weighted bipartite graph, as illustrated in Figure 4.5, where trips/drivers represent vertices. The edge weight matrix $W = [w_{di}, d \in D_t, i \in I_t]$ for the bipartite graph can be calculated using the road distance matrix derived from distances of each driver’s location to the trip origins.

![Figure 4.5: Weighted Bipartite Graph for Trips and Drivers at Each Time Step](image)

Since $|D_t| \geq |I_t|$, this is an unbalanced assignment problem, which can be formulated in (4.1).
\[
\min_{x \in \{0,1\}^{|I_t| \times |D_t|}} \sum_{(i,d) \in I_t \times D_t} w_{di}x_{di}, \quad \text{s.t. } \sum_{i \in I_t} x_{di} \leq 1, \forall d \in D_t; \quad \sum_{d \in D_t} x_{di} = 1, \forall i \in I_t. \tag{4.1}
\]

where \(x_{di}\) is a binary decision variable that determines if driver \(d\) is matched with trip \(i\) which values 1, and 0, otherwise. The objective function is designed to minimize the overall matching distance, and the constraints are formulated to ensure that each trip is assigned to precisely one driver, and each driver is paired with at most one trip.

To solve the problem (4.1) at each time step \(t\), we used the Hungarian algorithm, which is described in 3.

**Complete Outline to Estimate Charging Demand**

Firstly, we applied k-means clustering to discern typical work schedules of TNC drivers using an existing dataset with driver IDs. Subsequently, we employed the Hungarian algorithm to match drivers with riders at each time step, enabling the estimation of drivers’ trip-chain information for regions where trip-level data is available from the demand side. Lastly, we devised an agent-based simulation model incorporating forward-looking charging decision-making strategies to simulate drivers’ daily travel activity and derive estimates for the resulting spatial-temporal charging demand. The proposed methodology is summarized in Figure 4.6.

**Results from Case Study**

**Typical Work Schedules**

We utilized the RideAustin dataset to infer the typical work schedules of TNC drivers. While the RideAustin dataset provides an identifiable driver ID for each trip, explicit information on drivers’
working hours is not directly available. This limitation arises from the challenge of distinguishing stand-by time gaps from offline time gaps directly. Figure 4.7 illustrates the trip start/end times and trip durations.

Figure 4.8 displays the distribution of gap time for all trips in the Chicago metropolitan area. The distribution of trip gap time follows a pattern resembling a log-normal distribution, with the majority of trips having gap times less than 25 minutes. This implies that a driver is likely to receive a new trip within a 25-minute timeframe. Additionally, the distribution of gap time exhibits a long-tail pattern, suggesting instances of extended breaks and off-work periods.

We performed k-means clustering with the number of clusters \( K \) ranging from 1 to 8. The error sum of squares is depicted in Figure 4.9. Employing the "elbow" method, we discern that \( K = 3 \)
yields the most favorable clustering outcome. This determination is based on the observation that the addition of extra categories from $K = 2$ to $K = 3$ results in a substantial improvement in terms of the sum-of-squares error. However, the advantages of incorporating additional categories diminish at a faster rate when progressing from $K = 3$ to $K = 4$.

The breakpoints for $K = 3$ are 2.2 hours and 8.7 hours. $K = 3$ offers a natural interpretation of each category, i.e., stand-by periods ($t_{i,d}^g < 2.2$ hours), break periods ($2.2 \text{ hours} \geq t_{i,d}^g < 8.7$ hours) and off-work periods ($t_{i,d}^g \geq 8.7$ hours).

Figure 4.10 displays the sampled work schedules based on the outcomes of the k-means clustering. In defining a time duration as a work shift, we considered both ends of the shift as having time gaps greater than 2.2 hours. Various types of drivers can be identified in Figure 4.10. For instance, drivers 1 and 11 predominantly worked evening shifts; driver 9 engaged in two shifts separated
by a 4-hour dinner break; and driver 4 appeared to be a part-time driver, working shorter shifts. We processed the work schedules of all drivers, which will be utilized for bootstrapping when generating new drivers in the matching algorithm, as illustrated in Figure 4.4.

Driver-Trip Matching

In order to generate a synthetic driver population for the study area, it was necessary to have a distribution of driver working hours. Given the unavailability of this information for Chicago, we initially assumed that the distribution of working hours in Chicago mirrored that of Austin. Subsequently, we conducted a sensitivity analysis to explore the impact of different working hour distributions on charging demand.

The distribution of daily working hours for RideAustin drivers is depicted in Figure 4.11. The
Figure 4.9: Error Sum of Squares for Different Number of Clusters in k-means Clustering Algorithm

chart illustrates that a considerable number of drivers worked for a short period each day, with less than 1 hour being the norm for a significant portion. Only 13.2% of drivers worked for eight hours or more, and the majority of drivers worked for less than four hours per day.

We simulated the generation of drivers necessary to meet the daily trip demands in Chicago. The time resolution for start and end times in the Chicago TNC trip dataset was 15 minutes. To maintain consistency, the driver-trip matching algorithm (refer to Figure 4.4) assessed each exiting driver at 15-minute intervals to identify available drivers and introduced new drivers as needed to fulfill the trips.

The temporal variation of driver and trip numbers is depicted in Figure 4.12. It is evident that both trips and drivers exhibit a bi-modal distribution over time, with peaks at around 9 a.m. and 6 p.m.,
corresponding to the morning and afternoon traffic peak hours.

Following the matching of trips and drivers, each driver is assigned a sequence of trips to fulfill each day. The distribution of trips per driver is illustrated in Figure 4.13a. In order to assess the accuracy of our calculated distribution, we compared it with the actual TNC driver monthly reported trips, as depicted in Figure 4.13b. Notably, both distributions exhibit similar patterns, underscoring the potential of our proposed methodologies to generate a realistic driver workload.

It’s worth noting that the Chicago TNC driver data indicate a slightly larger number of drivers completing fewer trips. This discrepancy could be attributed to occasional drivers who work for fewer days than their counterparts, potentially skewing Figure 4.13b towards the right when scaling down monthly trip data to daily patterns.
Figure 4.11: Daily Working Hour Distribution

Figure 4.12: Distribution of Drivers and Trips in Chicago Across Time (time starts at 3:00 am)
To meet the demand for all 296,582 trips in the Chicago metropolitan area on the specified day, we simulate the operation of 21,029 TNC vehicles. Each vehicle, on average, completes 14.11 trips daily. The total daily vehicle miles traveled (VMT) amount to 1,850,932 miles, with an average daily VMT, including deadheading trips, of 88.02 miles per vehicle.

This suggests that EVs equipped with high-capacity batteries (such as Tesla S/3/X, Hyundai Kona Electric, Chevrolet Bolt, etc.) prove sufficient to cover most daily distances for electrified ridesourcing services in the Chicago area without requiring daytime charging. However, for the remaining EVs with average battery capacity (e.g., Honda Fit, Toyota Rav 4, etc.), daily charging, on average, becomes a necessity.

The summarized results for daily VMT and trips can be found in Table 4.1.
Table 4.1: Daily VMT and Trips Results

<table>
<thead>
<tr>
<th></th>
<th>Ride-sourcing</th>
</tr>
</thead>
<tbody>
<tr>
<td># of cars</td>
<td>21,029</td>
</tr>
<tr>
<td># of trips</td>
<td>296,582</td>
</tr>
<tr>
<td>Daily VMT (miles)</td>
<td>1,850,932</td>
</tr>
<tr>
<td>Daily VMT/trip (miles)</td>
<td>6.24</td>
</tr>
<tr>
<td>Daily VMT/car (miles)</td>
<td>88.02</td>
</tr>
</tbody>
</table>

Distribution of Charging Demand

The distribution of peak hourly public charging demand is illustrated in Figure 6.2. Notably, downtown Chicago and O’Hare International Airport exhibit comparatively higher charging demand than other areas.

Sensitivity Analysis

The finding of charging demand hinges on a critical assumption—the similarity of working hour distributions among TNC drivers in different regions, specifically Austin and Chicago. To assess the sensitivity of the results to regional variations, a thorough sensitivity analysis is undertaken. This analysis involves combinations of six distinct log-normal probability distributions, with mean working hours ranging from 3 to 8 hours.

The choice of the log-normal distribution is justified by the nature of working hours as non-negative variables, and the log-normal distribution being positively skewed with long right tails. Additionally, two scenarios for the initial State of Charge (SOC) are considered: random and constant. In the random scenario, the initial SOC is randomized between 40-100%, while in the constant
scenario, it has a uniform SOC of 100% (fully charged)

This sensitivity analysis will shed light on the impacts of these scenarios on three key aspects: VMT, peak public charging energy demand, and potential customers.

\[ VMT \]

Table 4.2 provides a summary of the required number of cars and daily VMT for various working hour scenarios. Notably, the number of drivers needed decreases as working hours increase—from 34,080 cars for the “3-hour” case to 16,489 for the “8-hour” case. However, this decrease is not proportionate to the increase in working hours.

39
For instance, while the total driver-hours needed to serve the same number of trips (296,582) for the "8-hour" case is 131,912 (calculated as 8 multiplied by 16,489) driver-hours, it is 102,240 (calculated as 3 multiplied by 34,080) driver-hours for the "3-hour" case. This suggests that as drivers work longer hours, the system may become less efficient, potentially resulting in increased cruising time.

The rise in total daily VMT with longer working hours leads to an increase in Daily VMT per trip (noting that the total number of trips remains constant for different working hour scenarios), ranging from approximately 6.22 to 7.18 miles. Our assumption that drivers plan for three trips, covering about 21 miles, is reasonable to allow drivers to find a charging station within the Chicago metropolitan area. As the number of cars needed decreases with longer working hours, the daily VMT per car in the "8-hour" case is almost 2.5 times (129.07 miles/car) that of the "3-hour" case (54.16 miles/car).

It’s worth noting that for both constant and random initial SOC, the total daily VMT, VMT per trip, and VMT per car are found to be almost identical. Therefore, Table 4.2 does not distinguish between constant and random initial SOC cases for brevity.

Table 4.2: Summary Statistics from Different Scenarios of Sensitivity Analysis

<table>
<thead>
<tr>
<th>Working hours</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td># of cars</td>
<td>34,080</td>
<td>26,244</td>
<td>21,700</td>
<td>19,034</td>
<td>17,129</td>
<td>16,489</td>
</tr>
<tr>
<td># of trips</td>
<td>296,582</td>
<td>296,582</td>
<td>296,582</td>
<td>296,582</td>
<td>296,582</td>
<td>296,582</td>
</tr>
<tr>
<td>Total Daily VMT (miles)</td>
<td>1,845,873</td>
<td>1,903,700</td>
<td>1,956,694</td>
<td>2,010,022</td>
<td>2,075,260</td>
<td>2,128,221</td>
</tr>
<tr>
<td>Daily VMT/trip (miles)</td>
<td>6.22</td>
<td>6.42</td>
<td>6.60</td>
<td>6.78</td>
<td>7.00</td>
<td>7.18</td>
</tr>
<tr>
<td>Daily VMT/car (miles)</td>
<td>54.16</td>
<td>72.54</td>
<td>90.17</td>
<td>105.60</td>
<td>121.15</td>
<td>129.07</td>
</tr>
</tbody>
</table>
Peak Public Charging Energy

Figure 4.15 displays heatmaps of peak public charging energy on an hourly basis for both the “3-hour” and “8-hour” scenarios. The visual representation highlights that downtown Chicago (referred to as “downtown”) and O’Hare International Airport areas exhibit significantly higher peak hourly public charging demand compared to other regions within the study area. In the context of this study, downtown Chicago encompasses the “Loop” (tract ID 8391) as the core, along with 14 surrounding tracts, as illustrated in Figure 4.16.

For the “3-hour” scenario, the peak charging energy in the downtown and airport areas increases from 77.65/195.7 kWh to 264.95/469.81 kWh when transitioning from a constant initial State of Charge (SOC) to a random initial SOC. Conversely, in the “8-hour” scenario, the peak charging energy decreases in these two locations. This trend may be attributed to the likelihood that, with longer working hours and a random initial SOC, drivers are more prone to needing to charge their vehicles before reaching downtown and the airport. In essence, the charging demand becomes more dispersed across various locations.

In general, an increase in working hours corresponds to higher peak public charging energy, as anticipated. This relationship is logical since longer working hours result in higher VMT per vehicle per day, as detailed in Table 4.2. As an illustration, at the airport, peak public charging energy rises from 195.7 kWh (mean working hour = 3) to 923.39 kWh (mean working hour = 8) in the constant case. However, it’s important to note that some variations are observed in the random case, reflecting the inherent randomness in the simulation process.
(a) Working Hours 3 with Constant Initial SOC

(b) Working Hours 3 with Random Initial SOC

(c) Working Hours 8 with Constant Initial SOC

(d) Working Hours 8 with Random Initial SOC

Figure 4.15: Heatmaps of Hourly Peak Public Charging Energy (kWh)
The current charging stations in the study area may fall short of meeting the charging needs, leading to unmet demand among TNC drivers—referred to as “potential customers.” The spatial distribution of potential customers within the study area is depicted in Figure 4.17. Similar to the patterns observed in peak public charging energy discussed in Section 4, downtown and the airport emerge as notable hotspots for potential customers.

As the mean working hours increase from 3 hours to 8 hours, both downtown and the airport
experience a higher number of potential customers, with downtown exhibiting a more significant increase. Specifically, the Chicago Loop (the Loop, tract ID 8391), at the core of downtown Chicago, emerges with the highest number of potential customers (refer to Figure 4.17) in both working hour scenarios. The Loop, being the second-largest commercial business district (CBD) in North America, spanning 1.58 square miles, houses the headquarters and regional offices of various global and national businesses, along with retail establishments, restaurants, hotels, and theaters.

Expanding the existing charging infrastructure in the Loop and its surrounding tracts may become imperative to support the full electrification of the ride-sourcing system. To alleviate range anxiety among TNC drivers, particularly those with trips to downtown and the airport, additional investment in charging infrastructure, especially in the Chicago Loop and its environs, is recommended.
(a) Mean Working Hours = 3 with Constant Initial SOC

(b) Mean Working Hours = 3 with Random Initial SOC

(c) Mean Working Hours = 8 with Constant Initial SOC

(d) Mean Working Hours = 8 with Random Initial SOC

Figure 4.17: Heatmaps of Potential Customer
Conclusions

We present a new methodology, integrating unsupervised learning, combinatorial optimization, and agent-based simulation to investigate the potential charging demand for electrified ride-sourcing services. This methodology can be used to estimate the charging demand from ride-sourcing BEVs given current travel patterns and charging infrastructure availability even if trip chain information is unavailable. Through a case study in the Chicago metropolitan area and sensitivity analyses, we find that

- Average daily vehicle miles traveled (VMT) per car could range from 54 miles to 129 miles depending on how many hours drivers work.

- Most of the existing BEV models can serve the average daily travel needs if the drivers start with a fully charged battery.

- Electrified ride-sourcing services may introduce significant public charging demand in the area of downtown Chicago and O’Hare International Airport.

- Downtown and Airport are two areas that experience relatively high unsatisfied charging demand.

Limitations and Future Research Direction

This research only focused on ride-sourcing services. Combining personal BEV trips, car sharing, and ride sharing may further overload the existing charging infrastructure and is worth investigating. Although a significant percentage of TNC drivers were part-time workers, our model can be adapted to handle more full-time drivers or even continuous operation of automated vehicles,
in which case we expect more charging demand from the ride-sourcing sector. In the short-term analysis, we aimed to gain a better understanding of the spatio-temporal distribution of charging demand given the penetration rate of ride-sourcing services. This information can be used for long-term charging infrastructure planning to optimize the charging facility siting and sizing to better serve the charging demand induced by an electrified ride-sourcing system. On the other hand, the long-term charging infrastructure planning will affect the EV adoption for ride-sourcing services, which will in return influence the distribution of charging demand. Gaining a better understanding of these short-term and long-term system interactions is a valuable next step to better prepare for an electrified transportation system.
CHAPTER 5: CHARGING FACILITY PLANNING

Problem Statement

Traditional CSAPs is not suitable for ride-sourcing systems because of different (VOT) at different locations and times due to dynamic pricing widely adopted by ride-sourcing companies. Therefore, the problem of interest in this chapter is to develop an integer programming (IP) model aiming to minimize the total system costs of development and equipment costs from an investor’s perspective and the charging and spatial-temporal VOT costs from a driver’s perspective.

Assumptions

In this study, the following assumptions were considered:

• The charging infrastructure planning was exclusively conducted for ride-sourcing vehicles.

• Candidate charging locations were deducted from the simulation of one-day trip data and a single charger type was assumed in the optimization model.

• Ride-sourcing drivers need to charge at the en-route charging station at most once a day because most of the BEV technologies nowadays are able to support the daily ride-sourcing energy demand by one-time charging that was found in the previous chapter.

• The Average lifespan of the charging station was assumed 5 years considering a more conservative estimation for charging station planning. Although Level 1/2 chargers have an expected lifespan of 10 years, fast charging station requires more maintenance compared with Level 1/2 chargers.
• To prevent potential permanent loss of battery capacity, a minimum allowable battery SOC of 20% was assumed.

• TNC drivers leveraged the dwell time (non-working time) effectively for charging activities so that all the original trips could be served.

Methodology

Formulation of Mixed-integer Programming Model

We aim to enhance the efficiency of charging station placement and sizing within a metropolitan area to meet the charging requirements of a fleet of ride-sourcing electric vehicles, taking into account the varying spatio-temporal values of VOT costs. Given that the decisions related to charging station locations are binary, and sizing involves integer variables, we have introduced an IP model.

Denote sets for ride-sourcing EV fleet, candidate charging locations, and time horizon as $I$, $N$, and $T$, respectively. The set $I$ specifically encompasses ride-sourcing drivers with a requirement for charging at some point during the day. This targeted inclusion is deliberate, as drivers without a charging demand do not exert any influence on the planning of charging stations. This focused approach enables us to directly tackle the charging needs of individual vehicles without introducing computational complexities. Three binary decision variables are defined: $x_{i,n,t}$ describes if vehicle $i$ decides to charge at location $n$ at time $t$, $z_{i,n,m,t}$ describes if vehicle $i$ relocate from $n$ to $m$ at time $t$ for charging services, and $y_n$ describes if a charging station is deployed at location $n$. In addition, an integer variable $s_n$ describes the number of installed charging plugs at location $n$. The IP model we have constructed is presented in the formulation denoted as the model (5.1). This model serves to ascertain the most effective strategies for planning charging infrastructure, determining optimal charging station locations, and specifying the number of plugs required to sustain electrified ride-
sourcing systems.

\[
\begin{align*}
\text{minimize} & \quad \sum_{n \in \mathcal{N}} C^D_n y_n + \sum_{n \in \mathcal{N}} C^E_n s_n + \sum_{i \in \mathcal{I}} \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} C^C_{n,t} e_{i,t} x_{i,n,t} + \\
& \quad \sum_{i \in \mathcal{I}} \sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{N}} \sum_{t \in \mathcal{T}} \left( T_m e_{i,t} + \frac{d_{n,m}}{v_{n,m,t}} \right) w_{n,t} z_{i,n,m,t}
\end{align*}
\] (5.1a)

subject to

\[
x_{i,n,t} \leq y_n \quad \forall i \in \mathcal{I}, n \in \mathcal{N}, t \in \mathcal{T}
\] (5.1b)

\[
\sum_{n \in \mathcal{N}} y_n \leq N_c
\] (5.1c)

\[
\sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{N}} \sum_{t \in \mathcal{T}} z_{i,n,m,t} = 1 \quad \forall i \in \mathcal{I}
\] (5.1d)

\[
z_{i,n,m,t} \leq x_{i,n,m,t} + \left\lceil \frac{d_{n,m}}{v_{n,m,t}} \right\rceil \quad \forall i \in \mathcal{I}, n \in \mathcal{N}, m \in \mathcal{N}, t \leq t_{max} - \left\lceil \frac{d_{n,m}}{v_{n,m,t}} \right\rceil
\] (5.1e)

\[
z_{i,n,m,t} = 0 \quad \forall i \in \mathcal{I}, n \in \mathcal{N}, m \in \mathcal{N}, t > t_{max} - \left\lceil \frac{d_{n,m}}{v_{n,m,t}} \right\rceil
\] (5.1f)

\[
z_{i,n,m,t} \leq a_{i,n,t} \quad \forall i \in \mathcal{I}, n \in \mathcal{N}, t \in \mathcal{T}
\] (5.1g)

\[
s_n \leq \hat{s}_n y_n \quad \forall n \in \mathcal{N}
\] (5.1h)

\[
s_n \geq \sum_{i \in \mathcal{I}} x_{i,n,t} \quad \forall t \in \mathcal{T}, \forall n \in \mathcal{N}
\] (5.1i)

\[
x_{i,n,t} \in \{0, 1\} \quad \forall i \in \mathcal{I}, n \in \mathcal{N}, t \in \mathcal{T}
\] (5.1j)

\[
z_{i,n,m,t} \in \{0, 1\} \quad \forall i \in \mathcal{I}, n \in \mathcal{N}, m \in \mathcal{N}, t \in \mathcal{T}
\] (5.1k)

\[
y_n \in \{0, 1\} \quad \forall n \in \mathcal{N}
\] (5.1l)

\[
s_n \in \mathbb{Z}^+ \quad \forall n \in \mathcal{N}
\] (5.1m)

where:

\[
C^D_n \quad : \text{proportional charging station development costs at location } n (\text{e.g., site survey, land}
\]
procurement, and construction costs) for time horizon $T$;

$C^E_n$: proportional charging station equipment costs at location $n$ (e.g., charging plug, credit card reader, and software connection costs) for time horizon $T$;

$C_{n,t}^C$: unit charging prices at location $n$ at time $t$;

e$_{i,t}$: charging energy demand at for vehicle $i$ at time $t$;

$w_{n,t}$: value of unit time at location $n$ and time $t$;

$\hat{s}_n$: the maximum number of charging plugs allowed to be installed at location $n$ due to space and power system constraints;

$T_m$: time required to charge one unit of energy at location $m$;

d$_{n,m}$: travel distance between location $n$ and $m$;

$v_{n,m,t}$: average speed of EVs from location $n$ to $m$ at time $t$;

$N_c$: maximum number of charging stations allowed to be developed in the study area;

t$_{max}$: the largest time index in $T$;

$a_{i,n,t}$: binary parameters indicating if charging at location $n$ and time $t$ is a feasible plan for vehicle $i$ to fulfill its future energy needs (1: true; 0: false);

$x_{i,n,t}$: binary decision variables indicating whether vehicle $i$ recharges battery at location $n$ at time $t$ (1: true; 0: false);

$z_{i,n,m,t}$: binary decision variables indicating whether vehicle $i$ relocates from location $n$ to $m$ at time $t$ to recharge the battery (1: true; 0: false);

$y_n$: binary decision variables indicating whether the charging station is deployed at location $n$ (1: true; 0: false);

$s_n$: decision variables on the number of charging plugs installed at location $n$
**Objective Function**

The objective function (6.1) minimizes the total costs from CS infrastructure investment (development and equipment costs), EV charging, and VOT for the time spent to charge (including charging time and relocation time). \( \sum_{n \in N} C_D \cdot y_n \) represents the total development cost (e.g., land costs) for all CS, \( \sum_{n \in N} C_E \cdot s_n \) represents the total equipment cost of charging plugs installed in these CS, \( \sum_{i \in I} \sum_{n \in N} \sum_{t \in T} C_C \cdot e_i \cdot t \cdot x_{i,n,t} \) represents EV charging costs, and \( \sum_{i \in I} \sum_{n \in N} \sum_{m \in N} \sum_{t \in T} \left( t_m \cdot e_{i,t} + \frac{d_{n,m}}{v_{n,m,t}} \right) z_{i,n,m,t} \cdot w_{n,t} \) represents the VOT costs due to charging time (i.e., \( t_{m,t} \cdot e_{i,t} \)) and relocation time (i.e., \( d_{n,m} \cdot v_{n,m,t} \)). Note that if the driver decides to charge at CS location \( n \) of the first attempt, \( z_{i,n,n,t} = 1 \). As \( d_{n,n} \) is equal to zero, there is no associated VOT cost for relocation.

**Constraints**

Constraint (5.1b) guarantees that a driver is permitted to charge only at locations where charging stations have been deployed. Constraint (5.1c) restricts the maximum number of charging stations that can be deployed based on regional plans and budget considerations.

Constraint (5.1d) specifies that a driver, denoted as \( i \), at location \( n \) and time \( t \) will relocate to location \( m \) for charging only once over the study time horizon \( T \). If \( n = m \), the driver will remain at the current location \( n \) for charging. This constraint is imposed under the assumption that a ride-sourcing driver typically needs to charge at public places at most once a day without loss of generality. This assumption aligns with the findings from [6], which indicate that most contemporary EV technologies can meet the daily energy requirements of ride-sourcing with a single charging session. Additionally, the constraint considers the practical challenges associated with multiple charging sessions, such as increased charging time due to station navigation and relocation.
Constraints (5.1e) establish the relationship between \( z \) and \( x \), indicating that if a vehicle relocates from \( n \) to \( m \) at time \( t \), it will arrive at location \( m \) at \( t + \frac{d_{n,m}}{v_{n,m,t}} \) and commence charging. The relocation time is determined by the distance \( d_{n,m} \) and the average travel speed from \( n \) to \( m \) at time \( t \), denoted as \( v_{n,m,t} \). The assumption here is that ride-sourcing traffic does not significantly influence travel time, as it is not the dominant mode of transportation, and travel time is primarily dictated by background traffic.

Constraint (5.1f) ensures that drivers will arrive at their desired charging locations within the study horizon. Specifically, drivers will not attempt to relocate from location \( n \) to a charging station \( m \) at time \( t \) when \( t > t_{\text{max}} - \lceil \frac{d_{n,m}}{v_{n,m,t}} \rceil \), as they would not reach location \( m \) before \( t_{\text{max}} \).

Constraint (5.1g) indicates that drivers decide where to charge based on locations and times that allow them to fulfill their energy needs. The binary indicator \( a_{i,n,t} \) signifies whether charging at location \( n \) and time \( t \) is a feasible option for driver \( i \) to meet its remaining travel requirements. The estimation of \( a_{i,n,t} \) relies on historical travel data of ride-sourcing vehicles.

Constraints (5.1h) and (5.1i) are related to the installation of charging plugs. Constraint (5.1h) ensures that the number of charging plugs installed is less than the maximum allowed at the charging station. If no charging station is deployed at location \( n \) (i.e., \( y_n = 0 \)), no plugs will be installed. Constraint (5.1i) ensures that the number of plugs available at a charging station is greater than or equal to the number of EVs capable of charging at any given time step.

Constraints (5.1j)-(5.1l) enforce the binary nature of decision variables \( y_n, x_{i,n,t} \), and \( z_{i,n,m,t} \), while Constraint (5.1m) ensures that the number of charging plugs remains a non-negative integer.
Our objective is to optimize both the locations and sizing of charging stations within a metropolitan area, catering to the charging requirements of a fleet of ride-sourcing EVs while accounting for the varying spatio-temporal costs of VOT. Recognizing the inherent dependence of planning decisions on the spatial-temporal dynamics of the system [97], we devised a trajectory-based model tailored for TNC vehicles. This model was subjected to simulation to identify potential charging locations and corresponding times.

Subsequently, the identified charging locations were organized into 20 clusters using the k-means clustering algorithm. The centroids of these clusters were then designated as candidate charging locations, forming the input for the optimization algorithm presented in Equation (5.1). This comprehensive approach allows us to consider both the spatial and temporal dimensions of the system, ultimately guiding the strategic placement and sizing of charging infrastructure for the ride-sourcing EV fleet.
Figure 5.1: Flowchart of Complete Process for CS Allocation

Result from Case Study

Charging Stations and Plugs Allocation

We successfully implemented and solved the charging station planning model with optimal (no optimality gap) decisions described in Equation (5.1) using Pyomo 5.6.7 [21] and CPLEX 20.1.0 [26], respectively. The presented case study demonstrates the completion of all trips. It is crucial to note that in scenarios with an extremely low budget limit and high charging demand, the model may become infeasible, leading to unmet charging demand.

Figure 5.2a visually represents the optimal locations of charging stations and the corresponding optimal number of plugs installed at each charging station for the base case. The analysis reveals that the optimal investment in charging stations is concentrated in four areas, specifically clusters
3, 5, 8, and 13. The optimal distribution of DCFC-50 charging plugs at these clusters is 1, 1, 2, and 1, respectively.

The decision to deploy only a limited number of charging stations and plugs stems from the high costs associated with DCFCs, and in the base case, the fleet size and the corresponding VOT costs may not be substantial enough to justify additional investments in charging infrastructure. The computed total development cost, equipment cost, and VOT cost are found to be $0.10/EV, $0.12/EV, and $21.75/EV, respectively. Notably, the VOT cost emerges as a significant component of the overall system costs. Consequently, disregarding VOT costs in the planning process for electrified ride-sourcing services may lead to biased and incomplete results.
Figure 5.2: Optimal Allocation of Charging Station and Plugs (Different Charger Types)
Sensitivity Analysis

Sensitivity analyses were conducted to comprehensively assess the influences of various factors on the total costs and optimal planning decisions for charging stations and plugs. The following parameters were considered in these analyses, building upon the base case, which involved the DCFC-50 charger:

- **Charger Types**: In addition to the DCFC-50 charger used in the base case, two other charger types, Level 2 (7.7 kW) and DCFC-150 (150 kW), were considered. The total charging station costs for Level 2 and DCFC-150 were determined as $2,500 and $75,600, respectively [67].

- **Fleet Sizes**: The analysis encompassed three different fleet sizes: 50, 100, and 150 vehicles. This variation allowed for an exploration of the impact of fleet size on the optimal charging infrastructure planning.

- **Government Incentives**: Government incentives ranging from 25% to 75% of the charging station development costs were included in the sensitivity analyses. This examination aimed to understand how varying levels of incentives affect the overall costs and planning decisions.

- **VOT Considerations**: The presence and absence of VOT considerations were compared, along with the evaluation of uniform and dynamic VOT scenarios. This analysis was crucial for understanding the role of VOT costs in the planning process and determining the optimal strategies accordingly.

By systematically varying these parameters and conducting sensitivity analyses, a comprehensive understanding of the charging infrastructure planning model’s response to different conditions was
achieved. This information is invaluable for making informed decisions and optimizing the charging infrastructure for ride-sourcing electric vehicle fleets in diverse scenarios.

Charger Types

The allocation of CS and EVSE is depicted in Figure 5.2. The case with Level 2 chargers exhibits the highest numbers of both CS and EVSE. Conversely, only two CS with a total of three DCFC-150 EVSEs are invested.

In Figure 5.3 and Table 5.1, the costs per electric vehicle (EV) and total costs are presented for different charger types. Notably, in Figure 5.3, charger types are ordered based on the incremental increase in charging speed: 7.7 kW (Level 2), 50 kW (DCFC-50), and 150 kW (DCFC-150). The development and equipment costs escalate, while VOT costs decrease with the increase in charging speed. This signifies a tradeoff between capital costs and consumer costs, indicating that faster chargers can save VOT costs by providing swifter charging services, albeit at a higher installation expense.

Although the development and equipment costs of a charging station are substantial, the daily total capital cost of this one-time expenditure remains low ($0.91 for Level 2 chargers, $6.9 for DCFC-50 chargers, and $24.2 for DCFC-150 chargers). The per-vehicle development and equipment costs individually amount to less than $1/EV, significantly lower than VOT costs. When Level 2 chargers are installed, the VOT cost is approximately $140/EV, reducing to $20/EV and $7/EV for DCFC-50 and DCFC-150 chargers, respectively. VOT costs are highest for Level 2 chargers due to their slower charging speed, even though they have the highest charging station density.

According to Table 5.1, the total system cost for Level 2 chargers is the highest ($21,972.68/day), while the cost is the lowest ($1,739.16/day) for DCFC-150. This suggests that higher-speed charg-
ing would be advantageous in supporting electrified ride-sourcing services, considering total system costs.

![Figure 5.3: Cost for Different Charger Types](image-url)

Table 5.1: Total Cost for Different Charger Types

<table>
<thead>
<tr>
<th>Charger Type</th>
<th>Total Cost ($/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 2</td>
<td>21,972.68</td>
</tr>
<tr>
<td>DCFC-50</td>
<td>3,877.19</td>
</tr>
<tr>
<td>DCFC-150</td>
<td>1,739.16</td>
</tr>
</tbody>
</table>
Figure 5.4 illustrates the optimized distribution of charging stations and the corresponding number of charging plugs for various fleet sizes. The assigned number of charging stations and plugs gradually rises as the fleet size expands from 50 to 150. This increase is driven by the heightened demand for charging resulting from larger fleet sizes. In the initial stages, when the fleet size is smaller, the planner prioritizes the downtown Austin area, where ride-sourcing vehicles are more likely to pass without significant detours. With an expanding fleet, the capital costs of additional charging infrastructure become more feasible due to the offsetting reduction in VOT costs. Consequently, there is a discernible shift towards more dispersed investment patterns of charging stations in Austin.

In Figure 5.5, the optimal total costs and costs per Electric Vehicle (EV) are depicted. With an increase in fleet size, a higher number of EVs necessitate charging, leading to elevated total VOT costs, as evidenced by the nearly linear relationship shown in Figure 5.5a. However, the VOT cost per EV remains stable across different fleet sizes, as demonstrated in Figure 5.5b. Concurrently, as the optimal allocation of charging stations and plugs rises with fleet size, there is an associated increase in total development costs and equipment costs. Nevertheless, the capital costs per EV experience a slight reduction, indicative of economies of scale in charging infrastructure investment.
Figure 5.4: Optimal Allocation of CS and Plugs from Different Fleet Sizes)
Simulations were conducted with three different incentive percentages, ranging from 25% to 75%, applied to charging station development and equipment costs. The impact of these incentives is evident in the optimal numbers of charging stations and plugs, which increase with higher incentive levels. For instance, at a 25% rebate, there are 4 stations with 6 plugs, while at a 75% rebate, the optimal numbers rise to 12 stations with 14 plugs, as depicted in Figure 5.6a - 5.6c.

Figure 5.7 provides a visual representation of the disparity in development costs and equipment costs per EV across varying incentive levels. For instance, a 75% incentive results in a 25% reduction in development costs and a 30% reduction in equipment costs per EV, compared to
scenarios with no incentives. This reduction is attributed to both a decrease in per-unit capital costs and an increase in the number of optimal charging stations and plugs. Moreover, the proliferation of charging stations and plugs contributes to a decrease in charging relocation time, consequently lowering VOT costs for EV drivers.

In summary, government incentives prove advantageous to both the charging infrastructure planner, by diminishing development and equipment costs, and EV drivers, by alleviating VOT costs.
Figure 5.6: Optimal Allocation of CS and Plugs from Different Incentives

(a) Charging infrastructure planning with 25% incentives

(b) Charging infrastructure planning with 50% incentives

(c) Charging infrastructure planning with 75% incentives
Figure 5.7: Costs from Different Incentives

Value of Time

The last sensitivity analysis in our study compares the sensitivity of the optimal results based on the consideration of VOT ($w_{n,t} = 0$ when VOT is not considered, $w_{n,t} > 0$ when VOT is considered). In addition, we consider two additional scenarios when VOT is considered: uniform VOT (average VOT $1.02$/minute) and spatio-temporal varying VOT.

Figure 5.8 demonstrates that when VOT is disregarded, the deployed charging infrastructure is reduced (specifically, 2 stations and 2 plugs). Consequently, more than 95% of EVs (149 in total) need to relocate to find a charging station. This situation significantly amplifies drivers’ VOT costs and diminishes their profits in practical terms. Given that VOT costs constitute a substantial
portion of the total system cost, neglecting VOT in the objective function of charging infrastructure planning for electrified ride-sourcing services fails to accurately mirror real costs and hampers the derivation of optimal charging infrastructure investment decisions. Hence, the inclusion of VOT costs is deemed indispensable.

Furthermore, when considering spatio-temporally varying VOT costs, the actual VOT costs derived from the optimal charging infrastructure plan are notably lower than those in the case of uniform $w_{n,t}$. Although the number of relocated vehicles is lower for the uniform $w_{n,t}$ case, drivers might need to relocate during peak hours when opportunity costs are high. Due to the fewer charging stations and charger plugs in the uniform scenario compared to the dynamic $w_{n,t}$ scenario, EV drivers may have to cover a longer distance during relocation, resulting in higher VOT costs. As such, the consideration of dynamic VOT costs provides a more nuanced understanding of the trade-offs involved in charging infrastructure planning.

<table>
<thead>
<tr>
<th></th>
<th>VOT not considered</th>
<th>VOT considered</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Uniform $w_{n,t}$</td>
<td>Dynamic $w_{n,t}$</td>
</tr>
<tr>
<td>VOT cost ($/day)</td>
<td>Not applicable</td>
<td>3,792.51</td>
<td>3,346.8</td>
</tr>
<tr>
<td>Development cost ($/day)</td>
<td>7.68</td>
<td>11.52</td>
<td>15.36</td>
</tr>
<tr>
<td>Equipment cost ($/day)</td>
<td>7.68</td>
<td>15.36</td>
<td>19.2</td>
</tr>
<tr>
<td>Charging cost ($/day)</td>
<td>492.8</td>
<td>492.8</td>
<td>492.8</td>
</tr>
<tr>
<td>Total cost ($/day)</td>
<td>508.16</td>
<td>4,312</td>
<td>3,874.16</td>
</tr>
<tr>
<td>Charging station number</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Charger plug number</td>
<td>2</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Number of relocated EVs</td>
<td>149</td>
<td>51</td>
<td>81</td>
</tr>
</tbody>
</table>

Figure 5.8: Sensitivity If VOT Is Considered or Not
Conclusions

We formulate an IP model for the allocation of charging stations and charging plugs for ridesourcing EVs. The model minimizes the total costs including development, equipment, charging, and VOT for charging and relocation by deciding the location of charging stations and the number of charging plugs to deploy. Through numerical examples based on RideAustin trip-chain data and sensitivity analyses on four key variables: charger types, fleet sizes, government incentives, and VOT considerations, we find that

- Four charging stations with five DCFC-50 charging plugs are optimal to minimize the total cost for the base case. The development cost, equipment cost, and VOT cost are found at $0.01/EV, $0.12/EV, and $21.75/EV, respectively.

- DCFC reduces the VOT cost compared with a slow charger. The VOT cost for Level 2 charging stations is $140/EV which can be reduced to $20/EV by using a DCFC-50 charger.

- With the fleet size increase, the charging investment pattern becomes more spread out. In addition, we observed slight economies of scale for charging infrastructure planning.

- When there is a higher percentage of government incentives, the optimal number of charging stations and charging plugs increase (four stations with six plugs at 25% to 12 stations with 14 plugs at 75% incentives), which also reduces the total capital costs for investors and VOT costs for drivers.

- When VOT is not considered, the optimization model cannot reflect the VOT cost, which leads to significantly biased investment results. The consideration of spatio-temporal varying VOT in CSAP allows more drivers to charge at the off-peak time, which reduces drivers’ VOT costs and the overall total system costs.
Limitations and Future Research Direction

We considered one-day trip data and single charger type. A large-scale study aggregating multiple days of uncertain ride-sourcing travel patterns with mixed charger types can be considered in future studies. We treated individual EVs in this study. To achieve better computational scalability when the EV fleet size is large, flow-based models can be proposed by grouping EV types into different categories. In addition, the model can be generalized by including queues due to other EVs at the charging station level to increase the model’s accuracy.
CHAPTER 6: FLEET OPERATION: PLATOONING AND CHARGING

SCHEDULING

Problem Statement

On one hand, long-haul EFVs need to spend long charging time along the route, which can provide flexibility for platooning coordination. On the other hand, the platooning of EFVs reduces the total energy consumption, which can effectively save the en-route charging time. Therefore, the problem of interest in this study is to explore the optimal charging and platooning strategies for a fleet of EFVs when they travel through a long-haul route to minimize the total cost incurred from en-route charging, hub charging and delivery delay. Charging scheduling determines the time, location, and duration for en-route charging while platooning scheduling determines when and where a vehicle enters/leaves a platoon.

Assumptions

In this study, the following assumptions were considered:

- Energy saving percentage of platooned vehicles was assumed uniform regardless of vehicle position. The main reason for this assumption is that vehicles could belong to different freight companies and vehicles in a platoon may need to switch positions to guarantee the fairness of energy savings.

- The battery of a vehicle was fully charged at the beginning of the trip, and the maximum and minimum SOCs were 95% and 20%, respectively.
• Unit price of electricity at the hub is cheaper than that of en-route charging.

Methodology

Formulation of Mixed-Integer Programming Model

We aim to co-optimize scheduling for charging and platooning of middle-mile EFVs at a network level with multiple OD pairs. We proposed a mixed integer programming (MIP) model to co-optimize the network-level scheduling of charging and platooning that will minimize the total system costs of en-route charging, hub (depot) charging, and penalty for late delivery. Furthermore, sensitivity analyses were conducted to understand the impacts of battery capacity, the number of EVSEs (i.e., CS capacity), charging speed, availability of alternative paths for OD pairs, and energy saving percentage of platooning.

Denote the freight transportation network as directed graph $G = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ is the node-set, including charging station nodes, highway interchanges, and freight origins/destinations, and $\mathcal{A}$ is the set of arcs, including the road links connecting the nodes. We focus on optimizing two major decisions of an electrified middle-mile EFV fleet, charging and platoon scheduling. The decision variable $t_{arr}^{j,s,p}$ represents the arrival time of a vehicle $j$ at a charging station $s$ along path $p$, and $t_{cha}^{j,s,p}$ is the charging duration. Apart from decision variables of charging schedule, the platooning binary decision variable $w_{j,s,s_{\text{next}},p}$ indicates if a vehicle $j$ is platooning on the road segment connecting $s$ and $s_{\text{next}}$ along path $p$. The binary variable $b_{j,p}$ indicates if vehicle $j$ chooses path $p$ or not. The objective of such charging and platoon scheduling minimize the total costs of en-route charging, hub charging, and delivery delay. In the remainder of this section, we will

\footnote{A path is a sequence of nodes that are traversed sequentially from the origin to the destination of a delivery trip. An origin-destination (OD) pair may have multiple alternative paths.}
present our mathematical formulation of the objective function and the constraints, together with a detailed explanation of their interpretation. All sets, variables, and parameters are listed in the nomenclature as follows.
Nomenclature

Sets and Indices

\( \mathcal{A}_p^{\text{platoonable}} \) set of links allowing for platoon along the path \( p \) represented by CS pairs \( (s, s_{s,p}^{\text{next}}) \)

\( \mathcal{J} \) set of electric freight vehicles

\( \mathcal{P} \) set of available paths

\( \mathcal{P}_j \) set of available paths for each vehicle \( j \)

\( S_p \) set of CSs on each path \( p \)

\( S \) set of CSs available in the entire network

\( \mathcal{T} \) set of time steps

Parameters

\( \delta \) percentage of energy saving from platooning

\( d_{s,s_{s,p}^{\text{next}}} \) distance between station \( s \) and \( s_{s,p}^{\text{next}} \), \( \forall s \in S_p \setminus \{s_{p}^{\text{dest}}\}, s_{s,p}^{\text{next}} \in S_p \setminus \{s_{p}^{\text{ori}}\}, p \in \mathcal{P} \)

\( M \) big number

\( m_j \) energy efficiency (kWh/mile) for vehicle \( j \)

\( n_s \) total number of electric vehicle supply equipment (EVSE) at a CS \( s \)

\( s_{j}^{\text{dest}} \) trip destination of vehicle \( j \)

\( s_p^{\text{dest}} \) destination CS of path \( p \)

\( s_{s,p}^{\text{next}} \) immediate next CS of each CS \( s \) along path \( p \)
$s^\text{ori}_j$  
trip origin of vehicle $j$

$s^\text{ori}_p$  
origin CS of path $p$

$SOC_{j}^{\text{arr, min}}$  
minimum required SOC of vehicle $j$ upon arrival at destination

$SOC_{j}^{\text{dep}}$  
SOC of vehicle $j$ during departure from depot i.e., origin

$SOC_{j}^{\text{min}} / SOC_{j}^{\text{max}}$  
allowable minimum/maximum SOC of vehicle $j$

$t^{\text{cha, min}} / t^{\text{cha, max}}$  
minimum/maximum charging time

$t_{j}^{\text{arr, max}}$  
latest time when a vehicle $j$ can arrive at final destination without late fee

$t_{j}^{\text{dep, min}} / t_{j}^{\text{dep, max}}$  
minimum /maximum departure time of vehicle $j$

$b^c_j$  
battery capacity of EFV $j$ in kWh

$c^\text{cha}_s$  
unit charging cost (per kWh) at en-route CS $s$

$c^\text{delay}_j$  
unit delivery delay (late fee per hour) cost for vehicle $j$

$c^e_j$  
unit electricity cost (per kWh) for vehicle $j$ during charging at depot

$r^{\text{cha}}_s$  
available charging speed (kW) from station (en-route/hub) $s$

$t_\tau$  
time at a time step $\tau$.

$v_j$  
average speed of vehicle $j$

**Variables**

$b^{1}_{j,j',s,p}$  
binary variable if vehicle $j$ and another vehicle $j'$ depart from a charging station $s$ concurrently in path $p$
\( b_{j,j',s, p}^2 \) binary variable if vehicle \( j \) and another vehicle \( j' \) arrive at next charging station \( s_{next}^{p} \) concurrently in path \( p \)

\( b_{j,j',s, p}^{\text{comb}} \) binary variable if both \( b_{j,j',s, p}^1 \) and \( b_{j,j',s, p}^2 \) are true, i.e., vehicle \( j \) and \( j' \) platoon together.

\( b_{j, p} \) binary variable if vehicle \( j \) chooses path \( p \)

\( c_{j,s,p, \tau}^1 \) binary variable if a vehicle \( j \) has arrived at en-route CS \( s \) in path \( p \) during time step \( \tau \), \( \forall s \in S_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\} \)

\( c_{j,s,p, \tau}^2 \) binary variable if a vehicle \( j \) hasn’t finished charging at en-route CS \( s \) along path \( p \) during time step \( \tau \), \( \forall s \in S_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\} \)

\( c_{j,s,p, \tau} \) binary variable if a vehicle \( j \) has arrived and hasn’t finished charging at CS \( s \) along path \( p \) at time step \( \tau \), \( \forall s \in S \)

\( \text{soc}_{j,s,p}^{\text{dep}} / \text{soc}_{j,s,p}^{\text{arr}} \) battery state of charge (SOC) of vehicle \( j \) when it departs/arrives at CS \( s \) along path \( p \)

\( t_{j,s,p}^{\text{cha}} \) charging duration of vehicle \( j \) at en-route CS \( s \) along path \( p \)

\( t_{j,s,p}^{\text{wait}} \) waiting duration of vehicle \( j \) at station \( s \) along path \( p \)

\( t_{j,s,p}^{\text{dep}} / t_{j,s,p}^{\text{arr}} \) time when a vehicle \( j \) departs/arrives at station \( s \) along path \( p \)

\( w_{j,s,s_{next}^{p}} \) binary variable if vehicle \( j \) joins platoon between CSs \( s \) and \( s_{next}^{p} \) along path \( p \)

\( z_{j,s,p} \) binary variable if a vehicle \( j \) decides to charge at CS \( s \) along path \( p \)
Objective Function

The objective function (6.1) minimizes the total cost for all the OD pairs. The total cost includes the en-route charging cost, formulated as \[ \sum_{j \in J} \sum_{p \in P_j} \sum_{s \in S_p} c_{s}^{\text{cha}} t_{j,s,p} \text{cha}, \] delivery delay cost, formulated as \[ \sum_{j \in J} c_{\text{delay}}^{j} \left( t_{\text{arr},j,s}^{\text{dest}} - t_{\text{arr},j,s}^{\text{max}} \right)^{+}, \] and the hub charging cost, formulated as unit hub charging cost \[ c_j^{\text{e}} \] multiples the energy charged at the hub (see the remaining portion of the objective function (6.1)). For vehicle \( j \), the energy charged at the hub can be calculated as the total energy consumed without considering platooning \( \left( \sum_{p \in P_j} b_{j,p} \sum_{s \in S_p} d_{s,s_{\text{next}}} m_j \right) \) minus the energy saving if vehicles join platoons during their trips \( \left( \sum_{p \in P_j} \sum_{(s,s_{\text{next}}) \in A_{\text{platoonable}}} d_{s,s_{\text{next}}} m_j \delta w_{j,s,s_{\text{next}},p} \right) \) and minus the energy already charged en-route \( \left( \sum_{p \in P_j} \sum_{s \in S_p} d_{s,s_{\text{next}}} t_{j,s,p} \text{cha} \right) \).

\[
\begin{align*}
\min_{w,t,b} & \quad \sum_{j \in J} \sum_{p \in P_j} \sum_{s \in S_p} c_{s}^{\text{cha}} t_{j,s,p} \text{cha} + \sum_{j \in J} \sum_{p \in P_j} c_{\text{delay}}^{j} \left( t_{\text{arr},j,s}^{\text{dest}} - t_{\text{arr},j,s}^{\text{max}} \right)^{+} + \sum_{j \in J} c_j^{\text{e}} \left( \sum_{p \in P_j} b_{j,p} \sum_{s \in S_p} d_{s,s_{\text{next}}} m_j \right) \\
& \quad - \sum_{p \in P_j} \sum_{(s,s_{\text{next}}) \in A_{\text{platoonable}}} d_{s,s_{\text{next}}} m_j \delta w_{j,s,s_{\text{next}},p} - \sum_{p \in P_j} \sum_{s \in S_p} d_{s,s_{\text{next}}} t_{j,s,p} \text{cha} \right) 
\end{align*}
\]

(6.1)

Constraints

State of Charge (SOC)

A set of constraints (6.2)-(6.9) describe the changes in SOC values of vehicles during their movement on the network. Constraint (6.2) describes the SOC of a vehicle \( j \) when it departs the origin, whereas constraint (6.3) describes the minimum SOC when it arrives at the destination. For the selected path \( p \) of a vehicle \( j \), the change in SOC when charging at CS \( s \) is specified in constraint (6.4). The SOC when an EFV departs from en-route CS \( s \) is calculated by adding the arrival SOC at en-route CS \( s \) and the amount of energy that is charged at this CS. Constraints (6.5) and (6.6) spec-
ify the consumption of battery energy for traveling. When a vehicle moves from one CS to another one, the SOC at the arrival (next) CS is calculated by subtracting the amount of energy consumption from the SOC at the departure CS. This energy consumption not only depends on distance but also depends on the vehicle status (i.e. whether an EFV is platooned or not). As the vehicles can be owned by various logistics companies, platooned vehicles may need to share the energy savings regardless of their vehicle position. Therefore, we assume an average energy-saving percentage for platooned vehicles regardless of the vehicle position. Constraint (6.7) describes that a vehicle can only choose one path to complete the freight delivery in the road network. Constraints (6.8) and (6.9) describe the upper and lower bounds of SOC for both arrival and departure at a CS. The minimum and maximum SOC guarantees adequate energy buffers for EFVs and helps maintain battery health.

\[
\text{soc}_{j,s_{\text{ori}},p}^{\text{dep}} = \text{SOC}_{j}^{\text{dep}} \quad \forall j \in \mathcal{J}, p \in \mathcal{P}_j \tag{6.2}
\]

\[
\text{soc}_{j,s_{\text{dest}},p}^{\text{arr}} \geq \text{SOC}_{j}^{\text{arr,min}} \quad \forall j \in \mathcal{J}, p \in \mathcal{P}_j \tag{6.3}
\]

\[
-M(1 - b_{j,p}) \leq \text{soc}_{j,s_{\text{ori}},p}^{\text{dep}} - \text{soc}_{j,s_{\text{ori}},p}^{\text{arr}} - \frac{r_{\text{cha}}^s}{b_j^c} - \frac{r_{\text{cha}}^{s_{\text{ori}},p}}{b_j^c} \leq M(1 - b_{j,p}) \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_{\text{ori}}^p, s_{\text{dest}}^p\}, \quad p \in \mathcal{P}_j \tag{6.4}
\]

\[
\sum_{p \in \mathcal{P}_j} b_{j,p} = 1 \quad \forall j \in \mathcal{J} \tag{6.7}
\]

\[
\text{soc}_{j,s_{\text{ori}},p}^{\text{arr}} - \text{SOC}_{j}^{\text{min}} \geq -M(1 - b_{j,p}) \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_{\text{ori}}^p, s_{\text{dest}}^p\}, p \in \mathcal{P}_j \tag{6.8}
\]

\[
\text{SOC}_{j}^{\text{max}} - \text{soc}_{j,s_{\text{ori}},p}^{\text{dep}} \geq -M(1 - b_{j,p}) \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_{\text{ori}}^p, s_{\text{dest}}^p\}, p \in \mathcal{P}_j \tag{6.9}
\]
Capacitated CSs

Constraints (6.10)-(6.15) ensure the capacity constraint at charging stations. In constraints (6.10) and (6.11), the vehicle’s status of arriving and charging at CS \( s \) at time step \( \tau \) in path \( p \) is monitored by binary variables \( c^1_{j,s,p,\tau} \) and \( c^2_{j,s,p,\tau} \), respectively. For example, if \( t^\text{arr}_{j,s,p} \) is greater than \( t_\tau \), it means vehicle \( j \) has not arrived at CS \( s \) at time \( t_\tau \), therefore, \( c^1_{j,s,p,\tau} \) should equal to 0. If \( t^\text{arr}_{j,s,p} + t^\text{cha}_{j,s,p} \) is greater than \( t_\tau \), it means vehicle \( j \) has not finished charging at time \( t_\tau \), therefore, \( c^2_{j,s,p,\tau} \) should equal to 1. Constraints (7.7)-(7.9) specify that if and only if a vehicle has arrived (i.e., \( c^1_{j,s,p,\tau} = 1 \)) at a CS and has not finished charging (i.e., \( c^2_{j,s,p,\tau} = 1 \)) at a particular time step \( \tau \), the charging indicator \( c_{j,s,p,\tau} \) will be 1. Constraint (6.15) guarantees that at each time step, the maximum total number of vehicles that can charge at a CS is the EVSE (charging plug) number of the CS.

\[
\begin{align*}
- M(1 - c^1_{j,s,p,\tau}) & \leq t_\tau - t^\text{arr}_{j,s,p} \leq M c^1_{j,s,p,\tau}; \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\}, p \in \mathcal{P}_j, \tau \in \mathcal{T} \quad (6.10) \\
- M(1 - c^2_{j,s,p,\tau}) & \leq t^\text{arr}_{j,s,p} + t^\text{cha}_{j,s,p} - t_\tau \leq M c^2_{j,s,p,\tau}; \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\}, p \in \mathcal{P}_j, \tau \in \mathcal{T} \\
\end{align*}
\]

\[
\begin{align*}
c_{j,s,p,\tau} & \leq c^1_{j,s,p,\tau}; \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\}, p \in \mathcal{P}_j, \tau \in \mathcal{T} \quad (6.12) \\
c_{j,s,p,\tau} & \leq c^2_{j,s,p,\tau}; \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\}, p \in \mathcal{P}_j, \tau \in \mathcal{T} \quad (6.13) \\
c_{j,s,p,\tau} & \geq c^2_{j,s,p,\tau} + c^2_{j,s,p,\tau} - 1; \quad \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\}, p \in \mathcal{P}_j, \tau \in \mathcal{T} \quad (6.14) \\
\sum_{j \in \mathcal{J}} \sum_{p \in \mathcal{P}_j} c_{j,s,p,\tau} & \leq n_s; \quad \forall s \in \mathcal{S}, \tau \in \mathcal{T} \quad (6.15)
\end{align*}
\]

Time

Constraints (6.16)-(6.19) describe the time variables of each vehicle while traversing the path. In constraint (6.16), the time when a vehicle departs a CS along the selected path is calculated by adding the time when a vehicle arrives at the CS, the charging duration, and the duration of wait-
ing before the vehicle joins other vehicles to make a platoon. As maneuvering an EFV from the highway to drive to and out of a CS requires additional effort, it is suggested to avoid too many short-duration charging events. Therefore, we provide flexibility to set minimum and maximum charging duration in constraint (6.17). Constraint (6.18) specifies the time window for the departure from the trip origin for each vehicle. When \( t_{dep,min}^j = t_{dep,max}^j \), this departure time is fixed. Considering a vehicle is moving between two consecutive CSs, constraint (6.19) calculates the arrival time of the vehicle at the next CS by adding the departure time from the previous CS and the time for traveling in between.

\[
-M(1 - b_{j,p}) \leq t_{arr,j,s,p}^{ch} + t_{wait,j,s,p} - t_{dep,j,s,p}^\text{ch} \leq M(1 - b_{j,p}); \quad \forall j \in J, s \in S_p \setminus \{s_{ori}^p, s_{dest}^p\}, p \in P_j
\]

\[
t_{\text{cha,min}}^{j,s,p} \leq t_{\text{cha},j,s,p} \leq t_{\text{cha,max}}^{j,s,p}; \quad \forall j \in J, s \in S_p \setminus \{s_{ori}^p, s_{dest}^p\}, p \in P_j
\]

\[
t_{j, s, p}^{\text{dep,min}} \leq t_{j, s, p}^{\text{dep}} \leq t_{j, s, p}^{\text{dep,max}}; \quad \forall j \in J, p \in P_j
\]

\[
-M(1 - b_{j,p}) \leq t_{arr,j,s_{next}}^{j,p} - t_{j, s_{next}, p}^\text{dep} - d_{s, s_{next}} / v_j \leq M(1 - b_{j,p}); \quad \forall j \in J, s \in S_p \setminus \{s_{dest}^p\}, p \in P_j
\]

**Platoon Formation**

Constraints (6.20)-(6.25) describe the dynamics of platoon formation. Constraints (6.20) and (6.21) describe the conditions to determine vehicle platooning, i.e., two vehicles depart from the same CS and arrive at the next CS at the same time. Constraints (6.22)-(6.24) mean that the binary variable \( b_{j,j', s, s_{next}, p}^{\text{comb}} \) is true if both the platooning conditions are true. Constraint (6.25) describes the definition for a vehicle \( j \) joining a platoon between the road segment (link) connecting CS \( s \) and \( s_{next} \) along path \( p \). These constraints indicate that a minimum of two vehicles are needed for platooning.
\[ M(1 - b_{j,j',s,p}^1) \leq t_{j,s,p}^{\text{dep}} - t_{j',s,p}^{\text{dep}} \leq M(1 - b_{j,j',s,p}^1); \forall j, j' \in J \land j \neq j', s \in S_p \setminus \{s_{p}^{\text{dest}}\}, p \in P_j \]

\[ M(1 - b_{j,j',s,p}^2) \leq t_{j,s,p}^{\text{arr}} - t_{j',s,p}^{\text{arr}} \leq M(1 - b_{j,j',s,p}^2); \forall j, j' \in J \land j \neq j', s \in S_p \setminus \{s_{p}^{\text{dest}}\}, p \in P_j \]

\[ b_{j,j',s,s_{p}^{\text{next}}}^{\text{comb}} \leq b_{j,j',s,p}^1; \forall j, j' \in J \land j \neq j', s \in S_p \setminus \{s_{p}^{\text{dest}}\}, p \in P_j \]

\[ b_{j,j',s,s_{p}^{\text{next}}}^{\text{comb}} \leq b_{j,j',s,p}^2; \forall j, j' \in J \land j \neq j', s \in S_p \setminus \{s_{p}^{\text{dest}}\}, p \in P_j \]

\[ b_{j,j',s,s_{p}^{\text{next}}}^{\text{comb}} \geq b_{j,j',s,p}^1 + b_{j,j',s,p}^2 - 1; \forall j, j' \in J \land j \neq j', s \in S_p \setminus \{s_{p}^{\text{dest}}\}, p \in P_j \]

\[ \sum_{j' \in J} b_{j,j',s,s_{p}^{\text{next}}}^{\text{comb}} \geq w_{j,s,s_{p}^{\text{next}}}^{\text{comb}}; \forall j \in J \land j \neq j', s \in S_p \setminus \{s_{p}^{\text{dest}}\}, p \in P_j \]

We also note that the modeling strategy of the platooning formulation in this study is more general and can also be leveraged to model the single-route-single-OD problem in [3]. The comparison of the computational performance is presented in section 7.

**Variable Types**

A set of constraints (6.26-6.28) exhibits the behavior of binary variables which is “choosing either 0 or 1”. Constraints (6.26) help in defining platoon formation. Constraint (6.27) helps in defining the platooning state of each vehicle between segment \( s \) to \( s_{p}^{\text{next}} \). Constraint (6.28) is needed to define the capacity constraint at each CS. In addition, constraints (6.29)-(6.31) specify that the temporal decision variables are non-negative.
\[ b^{\text{comb}}_{j,j',s,s',p,p}, b^1_{j,j',s,s',p}, b^2_{j,j',s,s',p,p} \in \{0, 1\}; \forall j, j' \in \mathcal{J} \land j \neq j', s \in \mathcal{S}_p \setminus \{s_p^{\text{dest}}\}, p \in \mathcal{P}_j \]  
\[ w_{j,s,s',s',p,p} \in \{0, 1\}; \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_p^{\text{dest}}\}, p \in \mathcal{P}_j \]  
\[ c^1_{j,s,p,\tau}, c^2_{j,s,p,\tau}, c_{j,s,\tau} \in \{0, 1\}; \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_p^{\text{ori}}, s_p^{\text{dest}}\}, \tau \in \mathcal{T}, p \in \mathcal{P}_j \]  
\[ t^{\text{cha}}_{j,s,p,\tau}, t^{\text{wait}}_{j,s,p,\tau} \in \mathbb{R}_+; \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_p^{\text{ori}}, s_p^{\text{dest}}\}, \tau \in \mathcal{T}, p \in \mathcal{P}_j \]  
\[ t^{\text{dep}}_{j,s,p} \in \mathbb{R}_+; \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_p^{\text{dest}}\}, p \in \mathcal{P}_j \]  
\[ t^{\text{arr}}_{j,s,p} \in \mathbb{R}_+; \forall j \in \mathcal{J}, s \in \mathcal{S}_p \setminus \{s_p^{\text{ori}}\}, p \in \mathcal{P}_j \]  

Implementation through a Case Study

We implemented the above model in a real-world numerical example using the container number database (CND) [36], which has trip OD information for commercial trucks in the state of Florida. Considering 7-day trip information from the database, we retrieved the trips with a distance of over 350 miles within 24-hour time windows. These trips are found to be made between 12 origin-destination (OD) points (0 → 7, 1 → 0, 1 ↔ 2, 1 ↔ 3, 1 ↔ 4, 1 ↔ 5, 1 ↔ 6). Based on the shortest routes for these OD pairs using OpenStreetMap data, the freight network for our numerical study is shown in Figure 6.1a.

The node set of the freight network includes the origin/destination nodes, intersection nodes, and DC fast charger (DCFC) nodes. In total, 40 Charging stations within a 1-mile buffer distance from the road networks were identified. The closest charging stations within a 500m radius were further grouped for conciseness. The number of electric vehicle supply equipment (EVSE) units (i.e., charging plugs) at each charging station was retrieved from [https://afdc.energy.gov/data/](https://afdc.energy.gov/data/). Figure 6.1b shows the refined freight network for our case studies.

Table 6.1 describes the values of the parameters we considered in this numerical example. We
Figure 6.1: Road Network for Case Study
considered 30 EFVs for one-way middle-mile delivery trips in a 24-hour time window. The earliest
departure time from the origin was set at 6 AM. All EFVs had the same technical properties such
as a battery capacity of a 300-mile range, and a fuel efficiency of 1.5 kWh/mile, as collected from
the leading-edge automotive industries such as Tesla, Rivian, and Freightliner. The energy-saving
percentage was assumed 13% from platooning. We also assumed DCFCs with a charging speed of
250kW. There was no restriction on the maximum number of EFVs in a platoon to guarantee total
flexibility in making platoons. Each platoon needs a minimum of two EFVs to call it a “platoon”.
We assumed all EFVs and platoons had a uniform speed of 50 mph. We also assumed that all
EFVs would depart the origin with a fully recharged battery. However, the en-route battery SOC
was restricted by at most 95% and at least 20%. We further assumed no charging event was less
than 30 minutes and more than 54 minutes (charging time from SOC=0.2 to SOC=.95 considering
a charging speed of 250kW). Based on the current market, a cheaper charging facility was available
at the depot ($0.1165/kWh) than the expensive en-route charging ($0.4/kWh). A $50 unit cost per
hour was assumed for the delivery delay.

For the sake of tight formulation, the big $M$ parameters should be selected as small as possible,
while still big enough to not cut off feasible solutions. Because the SOC (arrival/departure) at
an en-route charging station can not be larger than 0.95, we select $M = 1$ for SOC constraints
(6.4)-(6.6) and (6.8)-(6.9). On the other hand, as we only consider an operation window of 24
hours, we select $M=25$ (hours) for time-variable-based constraints such as CS capacity constraints
(6.10)-(6.11), time constraints (6.16), (6.19), and platoon formation constraints (6.20)-(6.21). We
solved the problem using CPLEX 20.1.0 with an optimality gap stopping condition of 2%, MIP
solving emphasis on optimality, and RINS heuristic (improves upon the best solution found so far)
of 20 enabled from the CPLEX parameter setting (Cplex, 2020). A Linux-based computer with
the Intel Core i9-9900K octa-core processor and 64GB RAM was used for solving the model. The
model was solved in 8 minutes. In order to improve computational efficiency, the variable $w_{j,s,s_{n+1},p}$
Table 6.1: Parameter Values for Base Case

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Unit</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of vehicles</td>
<td>-</td>
<td>30</td>
</tr>
<tr>
<td>Number of en-route CSs</td>
<td>-</td>
<td>26</td>
</tr>
<tr>
<td>Number of EVSE in en-route CSs</td>
<td>-</td>
<td>1-22</td>
</tr>
<tr>
<td>Fuel efficiency of vehicles</td>
<td>kWh/mile</td>
<td>1.5</td>
</tr>
<tr>
<td>Battery capacity of vehicles</td>
<td>kWh</td>
<td>300</td>
</tr>
<tr>
<td>Charging speed</td>
<td>kW</td>
<td>250</td>
</tr>
<tr>
<td>Vehicle Speed</td>
<td>mph</td>
<td>50</td>
</tr>
<tr>
<td>Latest delivery time</td>
<td>Hours</td>
<td>12</td>
</tr>
<tr>
<td>Platoon’s energy saving percentage</td>
<td>%</td>
<td>13</td>
</tr>
<tr>
<td>Origin SOC</td>
<td>%</td>
<td>100</td>
</tr>
<tr>
<td>Minimum required SOC upon arrival at en-route CS</td>
<td>%</td>
<td>20</td>
</tr>
<tr>
<td>Maximum allowable SOC when a vehicle departs from an en-route CS</td>
<td>%</td>
<td>95</td>
</tr>
<tr>
<td>Timestamp duration</td>
<td>Minutes</td>
<td>30</td>
</tr>
<tr>
<td>En-route charging cost</td>
<td>$/kWh</td>
<td>0.4</td>
</tr>
<tr>
<td>Hub charging (home electricity) cost</td>
<td>$/kWh</td>
<td>0.1165</td>
</tr>
<tr>
<td>Delivery delay cost</td>
<td>$/hour</td>
<td>50</td>
</tr>
<tr>
<td>Minimum charging duration</td>
<td>hour</td>
<td>0.51</td>
</tr>
<tr>
<td>Maximum charging duration</td>
<td>hour</td>
<td>0.9</td>
</tr>
</tbody>
</table>

was considered zero as the warm start for all combinations of indexes, that solved the model in 74 seconds.

Result from Case Study

In the context of the base case, the optimal expenses for en-route charging, delivery delay, and hub charging were solved to be $4540, $558, and $826, respectively. Table 6.2 presents the charging time, charging duration, and CS location for each EFV. Each EFV opted for en-route charging on average 3 times during their trip with a mean of 35 minutes. The benefit of multiple times of charging is that the EFV can adjust their spatial-temporal locations for the purpose of joining with other EFVs to make a platoon and get energy-saving benefits.
Table 6.2: Optimal Charging Scheduling Plan

<table>
<thead>
<tr>
<th>Vehicle ID</th>
<th>CS ID</th>
<th>Charging time (hour)</th>
<th>Charging duration (minutes)</th>
<th>Vehicle ID</th>
<th>CS ID</th>
<th>Charging time (hour)</th>
<th>Charging duration (minutes)</th>
<th>Vehicle ID</th>
<th>CS ID</th>
<th>Charging time (hour)</th>
<th>Charging duration (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>CS39</td>
<td>2.64</td>
<td>32.60</td>
<td>9</td>
<td>CS10</td>
<td>2.82</td>
<td>39.52</td>
<td>20</td>
<td>CS13</td>
<td>10.20</td>
<td>30.60</td>
</tr>
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The charging demand at en-route CSs in the road network is shown in Figure 6.2. We observe that CSs in northwest Florida have higher charging demand. We also observe from Figure 6.1b that the CSs in northwest Florida are located at a larger gap distance (on average 45+ miles) compared with the remaining CSs (on average 20 miles). Therefore, EFVs have a higher tendency to charge at least once from one of the CSs in this region. In addition, from the OD demand data, it is found that most of the trips start from node 1 or end at node 1, which also contributes to the observation that northwest Florida has a higher charging demand.

Figure 6.3 provides the total number of platooned EFVs at each link (road segment) of the network. The coordination of platooned EFVs across various links is done in a way that maximizes
Figure 6.2: Charging Demand at CSs

overall energy savings while simultaneously minimizing potential delivery delays. The energy consumption with and without platooning is described in section 6.
Figure 6.3: Number of Platooned EFVs in Each Road Segment/Link
Sensitivity Analysis

We performed sensitivity analyses for enhanced comprehension of different important features: platooning, charging speed, battery capacity, charging station capacity, availability of alternative paths, and energy-saving percentage of the platoon on the system costs. The feature settings are available in the feature value column in Table 6.3. We compared with and without platooning in order to understand the importance of co-optimizing platooning and charging schedules for middle-mile EFVs. To demonstrate the potential value of alternative paths, we compare the results between the base case and adding three alternative paths for a particular OD pair. We compared the impact of platoon energy saving percentage on different costs considering 8%, 13%, and 18% energy saving levels. For the sensitivity analysis, various charging speeds were examined, including 150kW, 250kW, and 350kW. For sensitivity analyses of EFV models with different battery capacities, we considered EFVs with 250, 300, and 350kWh battery capacities. Finally, for sensitivity analyses of CS capacity, we compared the base case capacity with only 2 EVSE/CS. The results are shown in Table 6.3.

Platooning and Charging Scheduling

We consider three cases. Case “no platooning - no charging schedule” means EFVs do not platoon and do not optimize charging schedules. They will only charge at en-route CSs when they cannot reach the immediate next CS/destination with SOC above the minimum limit and they will recharge the batteries to maximum SOC. Case “no platoon - only charging schedule” means EFVs do not platoon but they will optimize their charging schedules. Case “platooning and charging schedule” means EFVs will co-optimize both platooning and charging schedules.

When the fleet operator considers the option of platooning along with charging scheduling (i.e.,
Table 6.3: Sensitivity Analysis

<table>
<thead>
<tr>
<th>Features</th>
<th>Feature values</th>
<th>En-route charging cost ($)</th>
<th>Relative change with base case</th>
<th>Delivery delay cost ($)</th>
<th>Relative change with base case</th>
<th>Hub charging cost ($)</th>
<th>Relative change with base case</th>
<th>Total cost ($)</th>
<th>Computation time (minutes)</th>
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<td>6683</td>
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<td>71.68%</td>
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<td>-40.44%</td>
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<td>23.63%</td>
<td>804</td>
<td>44.09%</td>
<td>833</td>
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<td>558</td>
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<td>1288</td>
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<td>832</td>
<td>0.73%</td>
<td>6651</td>
<td>66</td>
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<td>Charging speed</td>
<td>250kW</td>
<td>4540</td>
<td>0.00%</td>
<td>558</td>
<td>0.00%</td>
<td>826</td>
<td>0.00%</td>
<td>5924</td>
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<td>Charging speed</td>
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<td>673</td>
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<td>572</td>
<td>2.51%</td>
<td>687</td>
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<tr>
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<td>0.00%</td>
<td>5924</td>
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<tr>
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<td>4527</td>
<td>-0.29%</td>
<td>591</td>
<td>5.91%</td>
<td>832</td>
<td>0.73%</td>
<td>5951</td>
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<td>Current CS capacity</td>
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<td>558</td>
<td>0.00%</td>
<td>826</td>
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<td>5924</td>
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</tr>
<tr>
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<td>558</td>
<td>0.00%</td>
<td>826</td>
<td>0.00%</td>
<td>5924</td>
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<td>762</td>
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<tr>
<td></td>
<td>8%</td>
<td>4975</td>
<td>9.58%</td>
<td>581</td>
<td>4.12%</td>
<td>829</td>
<td>0.36%</td>
<td>6836</td>
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<td>0.00%</td>
<td>826</td>
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<td>467</td>
<td>-16.31%</td>
<td>836</td>
<td>1.21%</td>
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case “platooning and charging schedule”), the en-route charging cost and the delivery delay cost were lower compared with the case if platooning was not considered (i.e., case “no platoon - only charging schedule”). In the “no platoon - only charging schedule” case, compared to the “platooning and charging schedule” case, the en-route charging cost increased by about 24% and the delivery delay cost increased by about 44%. These results demonstrate the value of platooning to save energy consumption and charging time. If no platooning, the excess energy demand may need to be satisfied by the en-route charging, which causes extra charging time and additional delivery delay costs. It was also found that the hub charging cost was increased if platooning and charging schedules were co-optimized. Since hub charging was assumed to be cheaper in our study, EFVs will try to charge at the hub as much as possible instead of charging en route to minimize the total system costs. The same reasoning applies to the increased hub charging costs in the sensitivity analyses on other factors.

In the case of “no platooning - no charging schedule”, total en-route charging cost, hub charging cost, and delivery delay cost are found to be $6683, $958, and $492, respectively. Note that the hub charging demand is less than the cases when charging schedules are optimized. This is because EFVs have predefined charging behavior to completely recharge their batteries whenever they plug in. However, an un-optimized charging plan may cause more time spent on en-route charging that subsequently causes more delivery delay costs than the cases when charging schedules are optimized.

Multiple Alternative Paths

Multiple alternative paths can introduce more flexibility in the network for platooning and charging to optimize the total system cost. We added three alternative paths for the OD pair from node 1 to node 0 in the road network as shown in Figure 6.4. Among these paths, path 1 is the shortest,
followed by path 2 and then path 0. In contrast, only path 0 was considered in the base case. It is found that EFVs from node 1 to node 0 chose path 2 rather than path 1 and path 0. Since path 1 has less number of DCFCs and a longer distance between DCFCs, it causes limited charging availability and fewer platooning opportunity. On the other hand, path 0 has a comparatively higher traveling distance which requires higher energy consumption. In this particular test case, about 4% of the total system costs were decreased by introducing alternative paths for one OD pair.
Platoon Energy Saving Percentage

From the sensitivity analysis of platoon energy saving percentage, the en-route charging cost and the delivery delay cost increase when the energy-saving percentage decreases. As less energy saving from platooning necessitates more en-route charging, therefore, the total en-route charging cost increases. More en-route charging requires additional charging time that lengthens trip duration and may result in a delivery delay. It is also found that the hub charging cost is negatively correlated with the en-route charging cost, which is intuitive because more en-route charging demand will reduce hub charging needs.

Charging Speed

From the sensitivity analysis of different DCFC charging speeds of 150 to 350kW, the delivery delay cost decreases when the charging speed increases. By increasing the charging speed from 250kW to 350kW, we see about a 34% reduction in the delivery delay cost. This is because EFVs have less charging duration due to a higher charging speed and are presumed in-time delivery. Although the en-route charging cost and hub charging cost for a slower charging speed do not change much compared with the base case, en-route charging cost is significantly higher with a faster charging speed. The reason is because of the imposed minimum charging duration per charge such that an EFV will charge more at en-route CSs with higher charging speed.

Battery Capacity

Our observations indicate that EFVs with lower battery capacity experience higher en-route charging costs and delivery delay costs, while simultaneously witnessing a decrease in hub charging costs when compared to EFVs with higher battery capacity. EFVs with 250kWh battery capacity
caused about 11% higher en-route charging cost, about 3% higher delivery delay cost, and about 17% lower hub charging cost compared with EFVs equipped with 300kWh battery capacity. The rationale behind this observation is that EFVs with lower battery capacity need to recharge their battery more frequently to complete the delivery trip. Therefore, they have a higher en-route charging time, which causes higher delivery delays. On the other hand, the higher en-route charging will reduce the need for hub charging, so that hub charging cost is lower compared with high-capacity EFVs. In terms of computational time to solve the model, the EFVs with 250 kWh take 7 times more minutes than EFVs with 300 kWh, because the systems are less flexible and more charging decisions need to be optimized.

Capacity of CSs

We found that among the three components of total costs, en-route charging cost decreased by 0.29%, hub charging cost increased by 0.73%, and delivery cost increased by 5.91% in the limited charging capacity scenario. The reason behind the decreased en-route charging cost is because fewer opportunities to charge en-route, which eventually causes more charging in the hub to restore battery SOC before the next trip. The total charging costs (including en-route charging cost and hub charging cost) increased when each CS only has a capacity of 2 EVSEs. This is because limited charging capacity leads to limited charging opportunities, which reduces the opportunities to coordinate platooning; less platooning will increase the total energy consumption. Delay costs increase because EFVs may experience charging congestion en-route due to the limitation of EVSE capacity and may have to wait for charging opportunities at en-route CSs.
Solving Strategy for Large-scale Model Instance

In the context of small-scale case studies, exact techniques are applied through the utilization of commercial global optimization (black-box) solvers, such as Gurobi and CPLEX. These exact methods offer a guarantee of identifying all optimal solutions, and the mathematical proof of solution optimality is attainable. Nevertheless, when dealing with larger-scale problems, traditional exact methods tend to become time-intensive. In such scenarios, the utilization of meta-heuristic algorithms and hybrid combinations of multiple meta-heuristic algorithms becomes a viable strategy to obtain solutions of acceptable quality for practical applications.

Upon addressing the proposed model, three strategies emerge as potential recommendations: fine-tuning the parameters of CPLEX, implementing a warm start approach, and employing hybrid metaheuristics that combine variable neighborhood search (VNS) with local branching.

**Tuning CPLEX Parameters**

CPLEX offers a wide array of parameters that enable users to customize the behavior of the CPLEX branch and bound algorithm. While these parameters provide numerous avenues for enhancing performance, two common approaches to tune these parameters are auto-tuning and a trial-and-error process.

One parameter, known as the Relaxation Induced Neighborhood Search (RINS) heuristic, was set to a small value, such as 20, indicating that the RINS heuristic will be applied after every 20 nodes. The RINS heuristic aims to improve the current best solution by exploring a neighborhood around the current incumbent solution in an effort to discover a superior solution.

Another parameter, the MIP Emphasis Switch, was set to 1, indicating a preference for finding an
optimal solution during the solving process. This parameter allows users to control the trade-offs between speed, feasibility, optimality, and the adjustment of bounds in the MIP-solving process. In this case, setting it to 1 implies a strong inclination towards finding the optimal solution.

**Warm Start Approach**

The observed difficulty in finding the initial incumbent solution for our MIP model using the CPLEX solver is a common issue, especially for large-scale instances. This problem can significantly impact the overall solution time. Additionally, when dealing with large instances, the memory (RAM) requirements can become a challenge due to the continuous growth of the branch and bound tree.

To address these issues, a valuable strategy is to provide the solver with a warm start. A warm start involves initializing the solver with an initial feasible solution before the optimization process begins. This can help in multiple ways:

- **Speeding Up the Solver**: Providing an initial feasible solution can greatly expedite the solver’s search for an incumbent solution. It gives the solver a starting point that is already close to a feasible solution, reducing the time spent exploring the search space.

- **Memory Efficiency**: With a warm start, the solver may not need to branch and bound as extensively, which can help in avoiding excessive memory consumption, particularly for large instances.

A feasible decision variable \( f_{comb}^{j,j',s,p} = 0 \) was considered as an effective warm start for our MIP.
Motivated by the work presented in [37] and [48], we implemented a hybrid meta-heuristic algorithm that combines Variable Neighborhood Search (VNS) with the Local Branching algorithm.

To initiate this hybrid approach, we first obtained the initial incumbent solution using a black-box solver.

The Local Branching technique was employed to reduce the solution space introducing new linear branching constraints. These constraints leverage the binary variables present in a feasible solution to define a neighborhood of feasible solutions, which can comprise $2^k$ different solutions, with $k$ being the number of constraints. The branching process iterates as long as improvements in the objective function are observed within a specified time limit. If no improvements are seen, intensification (i.e., the reduction of the neighborhood) is executed. If the solution becomes infeasible, diversification (i.e., the expansion of the neighborhood) is applied.

A “move or not” step was executed to determine whether the solution obtained through local branching was superior to the initial incumbent solution. If it was, the local branching solution becomes the new incumbent. Otherwise, the neighborhood space was expanded.

Following the “move or not” step, the “shaking” step was carried out to search for a feasible solution in the vicinity of the incumbent solution. Any newly found incumbent solution was reintroduced into the local branching loop. If a feasible solution was not found or if the solution was infeasible, the search neighborhood was enlarged.

For a more comprehensive understanding of the VNS-Local Branching algorithm, detailed information can be found in [48]. Setting hyperparameters for this metaheuristic algorithm is a crucial and challenging task. The algorithm operates within a total time limit hyperparame-
ter, ‘total_time_limit’, and the local branching MIP loop runs within a fixed node time limit, ‘node_time_limit’. These two hyperparameters depend on the size of the model instance. For example, in the case of 120 vehicles, we considered a ‘total_time_limit’ of 7200 seconds and a ‘node_time_limit’ of 1800 seconds. The hyperparameter for the initial value of ‘k’, ‘k_cur’, is set to 1, and the step size for increasing ‘k’, ‘k_step’, was considered as 50. The algorithm is further detailed in Algorithm 2.
Algorithm 2 Hybrid of VNS and Local Branching Algorithm

\[ TL := \text{total\_time\_limit}; k\text{\_step} := 50; k\text{\_cur} := 1; UB := \infty; first := true; \]
\[ \text{stat} := \text{MIP\_SOLVE}(TL, UB, first, x\_opt, f\_opt) \]
\[ x\_cur = x\_opt, f\_cur = f\_opt \]
\[ \textbf{while elapsedtime < total\_time\_limit do} \]
\[ \quad \text{cont} := true; rhs := 1; first = false; \]
\[ \quad \textbf{while elapsedtime < node\_time\_limit do} \]
\[ \quad \quad \text{add local branch constraint: } \Delta(x, x\_cur) \leq rhs; UB := f\_cur; \]
\[ \quad \quad \text{stat} := \text{MIP\_SOLVE}(TL, UB, first, x\_next, f\_next); \]
\[ \quad \quad \textbf{if} \text{ Optimal solution is found } \textbf{then} \]
\[ \quad \quad \quad \text{reverse last local branch constraint into } \Delta(x, x\_cur) \geq rhs + 1; \]
\[ \quad \quad \quad x\_cur = x\_next; f\_cur = f\_next; rhs := 1; \]
\[ \quad \quad \textbf{else if} \text{ Feasible solution is found } \textbf{then} \]
\[ \quad \quad \quad \text{reverse last local branch constraint into } \Delta(x, x\_cur) \geq 1; \]
\[ \quad \quad \quad x\_cur := x\_next; f\_cur := f\_next; rhs := 1; \]
\[ \quad \quad \textbf{else if} \text{ Infeasible solution is found } \textbf{then} \]
\[ \quad \quad \quad \text{remove last local branch } rhs := rhs + 1; \]
\[ \quad \quad \textbf{else if} \text{ No solution is found } \textbf{then} \]
\[ \quad \quad \quad \text{cont} := false; \]
\[ \quad \textbf{end if} \]
\[ \textbf{end while} \]
\[ \textbf{if } f\_cur \leq f\_opt \textbf{ then} \]
\[ \quad x\_opt = x\_cur; f\_opt = f\_cur; k\_cur = k\_step; \]
\[ \textbf{else} \]
\[ \quad k\_cur := k\_cur + k\_step; \]
\[ \textbf{end if} \]
\[ \text{remove all added constraints}; \text{cont} := true; \]
\[ \textbf{while contand(elapsedtime < total\_time\_limit do} \]
\[ \quad \text{add constraints } k\_cur \leq \Delta(x, x\_opt) < k\_cur + k\_step; \]
\[ \quad UB := \infty; first := true; \]
\[ \quad \text{stat} := \text{MIP\_SOLVE}(TL, UB, first, x\_cur, f\_cur); \]
\[ \quad \textbf{if} \text{ Infeasible solution is found or no feasible solution is found } \textbf{then} \]
\[ \quad \quad \text{cont} := true; k\_cur := k\_cur + k\_step; \]
\[ \textbf{end if} \]
\[ \textbf{end while} \]
\[ \textbf{end while} \]
Table 6.4: Hyperparameters of Hybrid Metaheuristics and Its Performance Compared to CPLEX’s Exact Method with Warm Start and Tuned Solver Parameters

<table>
<thead>
<tr>
<th>Number of vehicles</th>
<th>node_time_limit (seconds)</th>
<th>total_time_limit (seconds)</th>
<th>Best objective value</th>
<th>Solution time (seconds)</th>
<th>Optimal objective</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>30</td>
<td>300</td>
<td>2388</td>
<td>18</td>
<td>2357</td>
</tr>
<tr>
<td>30</td>
<td>60</td>
<td>600</td>
<td>6102</td>
<td>74</td>
<td>5808</td>
</tr>
<tr>
<td>60</td>
<td>180</td>
<td>1200</td>
<td>13450</td>
<td>416</td>
<td>11617</td>
</tr>
<tr>
<td>120</td>
<td>2700</td>
<td>14400</td>
<td>27698</td>
<td>3600</td>
<td>23237</td>
</tr>
</tbody>
</table>

*Performance of Solving Strategies*

Incorporating a warm start approach into the CPLEX solver and tuning the solver parameter had proven to yield better performance compared to the hybrid metaheuristics of VNS and Local Branching. Through a trial-and-error process, various hyperparameters for the metaheuristics were experimented with the goal of obtaining solutions as close as possible to the optimal solution. The hyperparameters selected for this approach are outlined in Table 6.4.

It was also observed that for larger model instances with an increased number of vehicles, ‘node_time_limit’ and the ‘total_time_limit’ were increased. This adjustment allows us to attain better solutions.

This can be justified by Figure 6.5, it was observed that from model instances with a small number of vehicles (e.g., 10 and 30 vehicles), the best value found in each iteration was improving in a shorter time and became close to the solution found using CPLEX, compared with instances with a large number of vehicles (e.g., 60 and 120 vehicles). Although we did not run the metaheuristics algorithm for a long time to reach the close result of CPLEX, the trend can easily infer that instances with a large number of vehicles required a very large ‘total_time_limit’. Nevertheless, as CPLEX provided the optimal solution in a shorter time, even for large model instances, this can be said that the model’s structure is well-suited for CPLEX when coupled with a warm start and tuned solver parameters.
Figure 6.5: Improvement of Best Values Found in Iterations over Time in Metaheuristics and Optimal Value from CPLEX Exact Method with Warm Start and Tuned Solver Parameters

Conclusions

This chapter fills the critical research gap of network-level co-optimization for the scheduling of charging and platooning of EFVs. We propose a MIP model for co-optimizing the scheduling of charging and platooning considering middle-mile trips and transportation networks for EFVs. The model captures characteristics of the dynamics of EFVs on the network such as the delivery within time windows, battery SOC dynamics, and platoon formation at the platoonable links. The objective of the model is to minimize total costs including en-route charging, delivery delay, and hub charging costs. Warm start approach, tuning CPLEX parameter and a hybrid of VNS and Local Branching algorithm were applied to solve the proposed model within an acceptable time duration.
With the numerical example and sensitivity analyses using freight network data in Florida, we found that:

- The consideration of platoon scheduling in the model reduces about 24% of en-route charging cost and about 44% of delivery delay cost compared with only optimizing charging schedules.

- To optimally coordinate charging and platooning, EFVs needed to charge an average of 3 times in a single delivery trip with a mean of 35 minutes per charging session.

- In the base-case scenario with the existing CS infrastructure in the State of Florida, it was found that en-route CSs of northwest Florida have higher charging demand from middle-mile EFVs compared with other regions.

- Higher charging speed and battery capacity are technical features of transportation electrification that have the potential to significantly reduce delivery delay cost and en-route charging cost, respectively.

- Considering alternative paths for OD pairs has the potential to provide additional flexibility for coordinating platooning and charging to further reduce the total system costs.

Limitations and Future Research Direction

We considered a charging and platooning scheduling problem given the existing CSs. Future research could optimize the CSs siting and sizing to facilitate not only the EFV charging but also allow them to better form platooning. To enable real-time scheduling facing uncertainties, such as travel time and charging availability, the proposed model can be extended using stochastic programming approaches. This study assumes complete information on the vehicle schedules and
CSs. Information sharing between different vehicles, CS plug availability, traffic operators, and freight companies can be studied to understand how to achieve the desired system coordination in a realistic environment where EFVs may not be owned by a single company.
CHAPTER 7: EVSE PLANNING CONSIDERING UNCERTAINTY IN SCHEDULING

Problem Statement

In the long-term planning of EVSEs, many uncertainties of fleet operations such as trip demand, vehicle speed, CS availability etc. emerge in real-world scenarios. Therefore, the problem of interest in this chapter is to explore the optimal plan of EVSEs considering the uncertainties to minimize the total EVSE acquisition cost and expected recourse cost due to en-route and hub charging and delivery delay.

Assumptions

In this study, the following assumptions were considered:

- Uncertainties were considered for vehicle speed and platoon’s energy efficiency in two scenarios.
- One type of EVSE was assumed with a charging speed of 150kW.

Methodology

Formulation of Stochastic Mixed-Integer Programming Model

As we find that charging station influences platooning opportunity, we plan to strategically allocate Electric Vehicle Supply Equipment (EVSE) at charging stations for more efficient operations.
In long-term planning, this plan faces uncertainties such as travel speed, travel demand, platooning efficiency, etc. It became apparent that the uncertainties related to vehicle speed and energy efficiency, particularly during disasters, differ from those encountered in regular circumstances. For instance, during a hurricane evacuation, the traffic flow becomes unpredictable and often congested, resulting in significantly reduced vehicle speeds [88], typically ranging between 40 to 60 mph due to increased accidents at various stages of evacuation. This heightened traffic flow also leads to reduced inter-vehicle distances within platoons, thereby increasing energy savings significantly [19]. In contrast, under normal conditions, platooned vehicles typically maintain an average speed of around 75 mph [87].

Recognizing the variability in speed and energy efficiency within platooning, we have devised a two-stage stochastic model to address these uncertainties. We assume EVSE will be installed at those charging stations that operate in disaster time.

As shown in objective function 7.1 in the stochastic model, the first stage determines the optimal count of EVSE, denoted as $n_s$ to minimize the total purchasing cost of EVSE. This determination relies on an expected recourse function $Q(n)$ in the second stage, which closely resembles the scheduling model discussed in the preceding chapter. Various constraints, such as budget and space availability, influence the allowable quantity of EVSE, limited by the maximum number of EVSE indicated in constraint 7.2.

In the second stage objective function 7.4 is executed for different scenarios. It’s worth noting that the notation employed is identical to the fleet operation model, with the exception of the platooning decision variable $u_{j,s,s_{next}}$. 

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\[
\text{minimize } \sum_{s \in S} c_s^E n_s + Q(n) \quad (7.1)
\]

subject to
\[
\begin{align*}
n_s &\leq \hat{n}_s; \quad \forall s \in S \quad (7.2) \\
n_s &\in \mathbb{Z}_+; \quad \forall s \in S \quad (7.3)
\end{align*}
\]

where
\[
Q(n) = \mathbb{E}_\xi Q(n, \xi(w)) \quad (7.4)
\]
\[
Q(n, \xi(w)) = \text{minimize}_{u, t, b} \left( \sum_{j \in J} \sum_{p \in P} \sum_{s \in S_p} c_s^\text{cha} u_{s, s, p} + \sum_{j \in J} \sum_{p \in P} c_j^\text{delay} \left( t_{j, s}^{\text{arr}} - t_{j}^{\text{arr, max}} \right) + \sum_{j \in J} \left( \sum_{p \in P} \sum_{s \in S_p} d_{s, s, p} m_j \right) \right.
\]
\[
\left. - \sum_{p \in P} \sum_{(s, s') \in \mathcal{A}_p} d_{s, s', p} \delta(w) u_{s, s', p} - \sum_{p \in P} \sum_{s \in S_p} c_j^\text{cha} u_{s, s, p} \right)
\]

Constraints

All the constraints in this model mirror those found in fleet operations scheduling models. However, since the primary aim is to reduce the purchasing cost of EVSE, the model seeks to minimize the quantity of EVSE. Consequently, it becomes imperative to track each charging event which determines the necessity of EVSE. To formulate this constraint, we introduced a few new variables as outlined below.

\[c_{j, s, p, \tau}^3: \text{ binary variable if a vehicle } j \text{ has arrived at en-route CS } s \text{ in path } p \text{ after time step } \tau, \forall s \in S_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\}\]

\[c_{j, s, p, \tau}^4: \text{ binary variable if a vehicle } j \text{ has arrived at en-route CS } s \text{ in path } p \text{ before time step } \tau + 1, \forall s \in S_p \setminus \{s^\text{ori}_p, s^\text{dest}_p\}\]
\( c''_{j,s,p,\tau} \): binary variable if a vehicle \( j \) has arrived at en-route CS \( s \) in path \( p \) between time step \( \tau \) and \( \tau + 1 \), \( \forall s \in S_p \setminus \{s^o_p, s^d_p\} \)

\( c^5_{j,s,p,\tau} \): binary variable if a vehicle \( j \) has consumed charging energy at en-route CS \( s \) in path \( p \) at time step \( \tau \), \( \forall s \in S_p \setminus \{s^o_p, s^d_p\} \)

\( c^*_j,s,p,\tau \): binary variable if a vehicle \( j \) has arrived at en-route CS \( s \) in path \( p \) between time step \( \tau \) and \( \tau + 1 \) and consumed charging energy, \( \forall s \in S_p \setminus \{s^o_p, s^d_p\} \)

If a vehicle arrives at a CS after a specific timestamp (as specified in constraint 7.5) but before its immediate next timestamp (as outlined in constraint 7.6), the system will track that vehicle for that particular timestamp and CS, marking it with \( c''_{j,s,p,\tau} = 1 \) according to the constraints (7.7-7.9).

If a vehicle consumes charging energy at the CS during the time step, the constraint 7.10 dictates that \( c^5_{j,s,p,\tau} = 1 \). If the charging time is more than .0001hr (\( \epsilon \)), the charging event will be tracked. If the vehicle arrives at the CS between timestamps \( \tau \) and \( \tau + 1 \) and consumes charging energy, \( c^*_j,s,p,\tau = 1 \) as detailed in constraints (7.11 -7.13).

Constraint 7.14 serves as a complicating constraint that links the first and second stages, and determines the total number of vehicles that can be charged at a CS within a given timestamp. This number cannot exceed the capacity of the available EVSE units.
−M(1 − c_{j,s,p,τ}^3) ≤ t_{\text{arr}, j,s,p} − t_τ + ϵ ≤ Mc_{j,s,p,τ}^3; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.5)

−M(1 − c_{j,s,p,τ}^4) ≤ t_{τ+1} − t_{\text{arr}, j,s,p} ≤ Mc_{j,s,p,τ}^4; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.6)

c_{j,s,p,τ}' ≤ c_{j,s,p,τ}^3; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.7)

c_{j,s,p,τ}' ≤ c_{j,s,p,τ}^4; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.8)

c_{j,s,p,τ}' ≥ c_{j,s,p,τ}^3 + c_{j,s,p,τ}^4 − 1; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.9)

\text{tcha}_{j,s,p} − ϵ ≤ M\text{c}_{j,s,p,τ}^5; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.10)

c_{j,s,p,τ}^* ≤ c_{j,s,p,τ}^5; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.11)

c_{j,s,p,τ}^* ≤ c_{j,s,p,τ}'; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.12)

c_{j,s,p,τ}^* ≥ c_{j,s,p,τ}^5 + c_{j,s,p,τ}' − 1; \forall j ∈ J, s ∈ S_p \{s_p^\text{ori}, s_p^\text{dest}\}, p ∈ P_j, τ ∈ T (7.13)

\sum_{j ∈ J} \sum_{p ∈ P_j} c_{j,s,p,τ}^* ≤ n_s; \forall s ∈ S, τ ∈ T (7.14)

Implementation through a Numerical Example

We implemented the stochastic model for a numerical example that has a hypothetical road network depicted in Figure 7.1. In this scenario, we took into account ten vehicles distributed across five Origin-Destination (OD) pairs, namely (0 → 7, 1 → 0, 2 → 1, 3 → 1, and 6 → 1). The distances (measured in miles) between nodes are indicated along the edges. Emergency Charging Stations (CS) are positioned at various nodes within the network, with the exception of the nodes corresponding to the vehicles’ own origins and destinations.

The model parameters remain consistent with those in the fleet operational scheduling model. We
assumed a purchasing cost of $10,000 for the 150kW EVSE. The maximum limit of EVSE units at CSs was set at 10. Two scenarios were considered. In the first scenario (Scenario 1: e.g., evacuation period with 60% probability), vehicles were assumed to travel at a constant speed of 50 mph on all road segments, with platooned vehicles exhibiting 10% energy efficiency. In the second scenario (Scenario 2: e.g., regular time with 40% probability), vehicle speed was raised to 75 mph, and platooned vehicles demonstrated 8% energy efficiency.
The model was scripted in Python using the Pyomo library and solved using two approaches: (1) solving the extensive form of the stochastic model using CPLEX and (2) using the Progressive Hedging (PH) algorithm. We ran the model in a Linux-based computer equipped with an Intel Core i9-9900K octa-core processor and 64GB of RAM. While solving extensive form, the optimality gap stopping condition was considered 1% and the solving time was 55 minutes. For the PH algorithm, the termination threshold was also 1%, which solved the model in 5 minutes.

The optimal number of EVSEs is found 3, and they are located at charging stations CS7, CS8, and CS14. The total objective cost for this solution amounts to $31,948. Of this total cost, $30,000 accounts for the 3 EVSE units, while the remaining $1,948 covers the total costs of fleet operations objective function.

Performance Comparison between PH algorithm and Extensive Form Solution

The PH algorithm is a decomposition-based algorithm that decomposes a series of subproblems of model instances from different scenarios. Parallel computing can be applied to make the overall solution of the PH algorithm fast. We used mpi-sppy library that can apply PH in a parallel computing framework. We considered a penalty factor of the PH algorithm, $\rho = 75$, and a termination threshold, $\epsilon = 0.01$. On the other hand, an extensive form is a deterministic form of a stochastic model with a series of recourse functions for different scenarios and probabilities. The extensive form is then solved using any solver.

According to Figure 7.2, it is found that the PH algorithm provided the solution in just 5 minutes compared with 55 minutes from extensive form solution for our numerical example. This clear difference was achievable due to the combined effect of the implementation of the PH algorithm
This chapter fills the research gap of addressing uncertainties in scheduling for long-term EVSE planning. We propose a two-stage stochastic MIP model for finding an optimal number of DCFC EVSE at given charging stations in the network. The objective is to minimize the EVSE acquisition cost and expected recourse cost of en-route and hub charging and delivery delay. A decomposition-based PH algorithm in a parallel computing framework was applied to solve the model. The extensive form of the model was also solved using a CPLEX solver. With a hypothetical numerical example, we found that:

- The proposed two-stage stochastic model can address uncertainties of operational scheduling for long-term EVSE planning.
• PH algorithm with parallel computing framework can dramatically improve the computational time for solving the proposed model.

Limitations and Future Research Direction

In our hypothetical example, we only considered uncertainties in vehicle speed and energy efficiency percentage. The uncertain spatial-temporal charging demand generated from other EV vehicles could be considered in the real-world case study. New case studies for facility location planning with uncertainties in scheduling may need an extension of the proposed model by adding a new set of constraints and may challenge computational performance for specific studies. Besides PH algorithm, other state-of-the-art methodologies can be applied or new algorithms can be proposed.
CHAPTER 8: CONCLUSIONS

Summary

Electric vehicles, connected mobility, and shared mobility play pivotal roles in shaping the future of advanced transportation systems. This dissertation addresses research gaps that have not yet been explored in the context of transportation electrification for shared and connected mobility. Specifically, we address research gaps in charging infrastructure planning and charging/platooning scheduling for ride-sourcing and freight transportation sectors. As transportation electrification in shared and connected mobility is an emerging area, we also suggest research avenues based on our limitation of the aforementioned studies and relevant literature review [4].

This dissertation helps the power distribution system operators to revise their plan for an efficient power distribution. It helps the charging infrastructure company in terms of economy and societal service by strategically allocating the charging stations and plugs. Ride-sourcing companies and drivers are implicitly benefit and they become motivated to purchase more EVS and adapt to EV culture. Besides ride-sourcing companies, freight companies will benefit from the dissertation by reducing the energy consumption required in freight delivery. Road construction companies can pay attention while designing road segments with more traffic load from platooned EFVs. To increase the market share of charging infrastructure, charging infrastructure companies can efficiently plan for long-term infrastructure deployment considering uncertainties of traffic operations. Once all stakeholders become beneficiaries of transportation electrification, EVs will be easily adapted globally and sustainability and decarbonization in the transportation sector can be ensured.
Limitations and Recommendations

This dissertation addresses research gaps found in the widespread adoption of EVs in shared mobility and connected freight mobility. While conducting studies of chapters 4-7, we identified limitations and research directions described in a separate subsection at the end of each chapter. A summary of the overarching limitations and research direction across all chapters is provided below.

- In our studies, the proposed models considered centralized decision makers that may not be always true in the real world. The decisions can involve multiple stakeholders, such as charging station aggregators, power distribution systems operators, power generation companies, other freight companies/TNC drivers, etc. in a decentralized manner to optimize their objectives. To understand the interactions among stakeholders in future research, the game theoretical framework can be applied.

- Our operational scheduling studies considered charging and platooning scheduling. In shared and connected freight mobility, route optimization can also be studied for more efficient mobility. Given the continuous evolution of freight transportation, characterized by diverse logistics patterns, incorporating these variations into operational scheduling studies is also a valuable research avenue.

- The proposed two-stage stochastic model was implemented on a hypothetical example. Instead of a hypothetical example, we can study a real-world case study that may extend the model by adding a new set of constraints and may challenge computational performance for specific studies. Besides the PH algorithm, other state-of-the-art methodologies can be applied or new algorithms can be proposed.

- Solutions of planning/operational decision models can be validated through field experi-
ments (e.g., pilot studies). Validated results from pilot studies will further encourage more stakeholders in shared and connected mobility systems and promote EV adoption.
LIST OF REFERENCES


