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Data-driven analyses of future electric personal mobility

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Data-driven analyses of future electric personal mobility

by

Liang Hu

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Civil Engineering (Transportation Engineering)

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2019

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DEDICATION

In dedication to my wife and my parents.

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NOMENCLATURE

AV	Autonomous Vehicle
BEV	Battery Electric Vehicle
CGV	Conventional Gasoline Vehicle
CPT	Cumulative Prospect Theory
DOE	Department of Energy
DOT	Department of Transportation
DVMT	Daily Vehicle Miles Traveled
EAV	Electric Autonomous Vehicle
EIA	Energy Information Administration
EPA	Environmental Protection Agency
EV	Electric Vehicle
FHWA	Federal Highway Administration
GPS	Global Positioning System
NHTS	National Household Travel Survey
NN	Neural Networks
NYC	New York City
SAE	Society of Automotive Engineers
SOC	State-of-Charge
TOU	Time-of-Use

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ABSTRACT

Personal mobility is moving towards the era of electrification. Adopting electric vehicles (EV) is widely regarded as an effective solution to energy crisis and air pollution. Many automakers have announced their roadmap to electrification in the next 1-2 decades. At the same time, limited electric range and insufficient charging infrastructure are still obstacles to EV large-scale adoption. However, with the emerging technologies of ride-hailing, connected vehicles, and autonomous vehicles, these obstacles are being solved effectively, and the EV market penetration is expected to increase significantly. Among the many kinds of electric mobility, electric taxis and personal battery electric vehicles (BEV) especially are gaining increasing popularity and acceptance among customers. This dissertation studies the future challenges of electric taxis and personal BEVs.

First, this dissertation examines the BEV feasibility from the spatial-temporal travel patterns of taxis. The BEV feasibility of a taxi is quantified as the percentage of occupied trips that can be completed by BEVs during a year. It is found that taxis with certain characteristics are more suitable for switching to BEVs, such as fewer daily shifts, shorter daily driving distance, and higher likelihood to dwell at the borough of Manhattan. Second, we model and simulate the operations of electric autonomous vehicle (EAV) taxis. EAV taxis are dispatched by the optimization-based model and the neural network-based model. The neural network dispatch model is able to learn the optimal dispatch strategies and runs much faster. The EAV taxis dispatched by the neural network-based model can improve operational efficiency in term of less empty travel distance and smaller fleet size. Third, this dissertation proposes a cumulative prospect

theory (CPT) based modeling framework to describe charging behavior of BEV drivers. A BEV mass-market scenario is constructed using 2017 National Household Travel Survey data. By applying the CPT-based charging behavior model, we examine the battery state-of-charge when drivers decide to charge their vehicles, charging timing and locations, and charging power demand profiles under the mass-market scenario. In addition, sensitivity analyses with respect to drivers' risk attitude and public charger network coverage are conducted.

CHAPTER 1. INTRODUCTION

1.1. Background

1.1.1. Electric Vehicles

Electric vehicle is a kind of vehicle technology that uses electric motors for propulsion. Unlike conventional gasoline vehicles on which a fuel tank is installed, electric vehicles are powered by electricity that is stored in the onboard battery packs. This type of electric vehicles are also called pure electric vehicles or battery electric vehicles. The earliest EV came into existence in the mid-19th century, but in the past 100 years of automotive history, the internal combustion engines have been playing a dominant role in vehicle propulsion. In the 21st century, with the rise of environmental concerns and technological advancements in batteries, renewable energy, and vehicle powertrains, electric vehicles saw a resurgence and have been developing very fast (Neubauer et al., 2012).

Electric vehicles hold many advantages over conventional gasoline vehicles. First, electrified transportation will reduce the dependency on fossil fuels. Transportation is the one of the major sectors that consumes a large amount of fossil fuels every year and emits considerable greenhouse gas (GHG) emissions and air pollution (Ajanovic, 2015). Electric vehicles, by contrast, are powered by electricity that has more renewable power sources, such as hydraulic, nuclear, biomass, and wind (Raugei et al., 2018). In addition, the process of electricity consumption has zero emission. Second, EVs have simpler body structure and mechanism, thus making vehicle design, manufacture, and maintenance in easier ways (Bradley and Frank, 2009). Take Tesla Model 3, a popular EV model, as an example. The wheels are powered by the motors that are placed by the side of the wheels, so the complex transmission mechanism can be removed. The combustion engine is also eliminated and the

space under the hood is used as luggage compartment. Third, lower use cost. Although the start price of EVs is more expensive than gasoline cars due to the pricey battery packs, the cost of electricity is much cheaper than gasoline for driving the same distance. The lower use cost will attract more people to switch to EVs. When batteries become cheaper, the cost advantage of EVs will be even larger (Cano et al., 2018).

Due to the benefits of EVs, governments and auto manufacturers are taking serious steps to promote the adoption of EVs. Many countries give subsidies to personal EV buyers and public transit, such as electric taxis, electric buses, and electric delivery trucks (Palmer et al., 2018). New York City, Hong Kong, and Shenzhen, China are deploying electric vehicles for taxis (Yang et al., 2018). A large amount of electric buses have been hitting road in Norway for years (Bjerkan et al., 2016). Major automakers also announced their road map towards electrification. For example, Volvo aims at “fully electric” in the next 1-2 decades (Lambert, 2018). General Motors decided that their Cadillac brand will become the leading EV brand (Hawkins, 2019). This American largest automaker also took joint efforts with Ford and Nissan into EV research and development, hoping to create further competition for Tesla (Nolan, 2019). Zhang et al. (2017) forecasted that in the near future EV will be widely accepted and used for both public transit and personal travel.

However, electric vehicles are confronted with some obstacles. The first obstacle is the electric range limitation. A typical gasoline vehicle has 400~500 miles range on a full tank. The electric range of most EV models is much shorter due to the limitation of battery packs. The most-recent National Household Travel Survey (U.S. DOT, FHWA, 2017) conducted across the U.S. revealed that most EV customers are driving EVs of less than 100-mile range. Drivers who have long daily commute distance may not believe switching to EVs

is a feasible option. Second, charging technology and infrastructure. Refueling a gasoline vehicle takes only a few minutes and gas stations are located almost everywhere. However, charging EVs could take much longer time. The Level-1 chargers of less than 10 kW are currently the most popular chargers (SAE, 2016) and could take an entire night to fully charge an EV. The EV fast charging technology is still being developed and has not gained wide adoption due to safety concerns and potential burden to the power grid (Angelov et al., 2018). Moreover, charging infrastructure is far from enough to support the use of EVs at the current stage. Building charging stations is slow because EV market penetration is minimal. Drivers are not exposed to charging infrastructure very often, so they become more reluctant to switch to EVs. This is called the “chicken-and-egg” problem of electric mobility (Schüßler and Bogenberger, 2015). With the advances in batteries, fast charging, and wireless charging, range anxiety and charging inconvenience are believed to be relieved.

The obstacles to EV adoption force people to come up with new solutions. Providing electric mobility services is one of the most effective methods to promote the use of EVs. Instead of encouraging people to own electric vehicles, mobility services using EVs can also satisfy people’s travel demand, such as electric taxis and ride-hailing EVs. On the other hand, good charging service is the core for EV owners. Understanding the charging behavior of EV drivers will help provide better charging service to them.

1.1.2. Ride-hailing and Autonomous Vehicles

Using electric vehicles for mobility services becomes even more promising in recent years as the technology improvements of ride-hailing and autonomous vehicles start to accelerate. Ride-hailing platform connects passengers and local drivers who use their personal vehicles. Passengers request a ride-hailing vehicle through a smartphone app. The ride-hailing platform will assign a nearby driver to pick up the passengers. The information

of both passengers and vehicles are available to the platform, thus the travel demand of passengers can be better satisfied (e.g. shorter waiting time) and the efficiency of vehicle operations could improve (e.g. shorter cruising distance). When drivers use their personal EVs, the ride-hailing platform that keeps track of the real-time vehicle GPS can provide location-based service to the drivers, such as charging stations and idle chargers within the remaining range (Tian et al., 2016). The range anxiety of EV drivers could be relieved. On the side of passengers, their acceptance to EVs will also increase with more exposure to EV ride-hailing. A study showed that people with experience of using electric mobility services rate usefulness of EVs higher. Also, these people have stronger intention of buying EVs (Schlüter and Weyer, 2019).

Autonomous vehicle technology develops rapidly in recent years with the advances in artificial intelligence, robotics, and high-performance computing. Autonomous vehicles have the ability to drive through sensing and intelligence techniques residing in the vehicle with no external assistance from humans (Mahmassani, 2016). Autonomous vehicles are often discussed with connected vehicle systems, a technology that enables AVs to communicate with a background management center, other vehicles, and transportation infrastructure. For example, an electric AV can exchange information, e.g. locations and battery SOC, with charging stations, thus vehicle charging can be scheduled in advance and multiple charging sessions can be coordinated at the system-wide level (Ma et al., 2018). Autonomous vehicle technology will greatly improve the driving experience of EVs. A study showed that autonomous vehicles may increase the market share of BEVs (Lin and Xie, 2018). The industry has realized this potential and started to demonstrate the business strategy of electric and autonomous vehicles. Tesla is the pioneer who puts electric vehicles with the automated

driving function called Autopilot into market (Tesla, 2019). General Motors is testing the AV hardware and software on the Chevrolet Bolt EVs (Lambert, 2018). Waymo reinvented the Jaguar E-pace EV to an autonomous car and will use this EAV model for their ride-hailing service (Hawkins, 2018).

1.1.3. Future Electric Mobility

Personal mobility in the future will be reshaped by electric vehicles combined with other mobility technologies. In addition to private electric vehicles, various means of transportation using EVs have been studied or already implemented in practice. Taxis are usually pioneers that adopt new technology to improve its service. Jung et al. (2014) studied an electric taxi system and explored the effects of EV taxi fleet's operations on the charging system. They suggested that EV taxis can be a viable option to tackle the range limitation problem. Tian et al. (2016) collected EV taxi data in Shenzhen, China including the taxi real-time GPS trajectories and historical charging events. These data helped them build a real-time charging station recommendation system for EV taxis. Electric car-sharing is another emerging mobility service. The EV car-sharing services that people can already use include Daimler AG's Car2go, the EvCard in Shanghai, China, and the Autolib' in France (Wikipedia, 2019). The research in this field focused on the system design and the optimization methods for EV-sharing operations. For example, Boyacı et al. (2015) developed an optimization framework for planning an one-way EV car-sharing system, and Bruglieri et al. (2018) optimized the relocation of shared electric vehicles. In addition to EV sharing, there are also studies examining ride-hailing that uses electric vehicles to satisfy passengers' travel demand, though only a few at this moment (Jenn et al., 2018).

Electric vehicles alone may not fully satisfy people's transportation need and reduce traffic congestion. Some studies have focused on the assistance of AV technology to the

electric mobility services. Chen et al. (2016) conducted an agent-based simulation for a fleet of shared EAVs operating in Austin, Texas. Farhan and Chen (2018) expanded this research to EAV carpool. They revealed that EAV carpool can reduce fleet size and the number of charging stations significantly compared to the traditional ride-hailing service. Kang et al. (2017) also studied an EAV sharing system using an optimization framework. Iacobucci et al. (2018) modeled a one-way car sharing service using EAVs in Tokyo, Japan. In addition to EAV car-sharing, Jäger et al. (2017) focused on an EAV on-demand mobility system and simulated the vehicle operations.

1.2. Problem Statement

The challenges confronted with future personal electric mobility are three folds. First, can electric vehicles satisfy people's current transportation demand? How do electric taxis reshape the current gasoline taxi service? Second, with the introduction of autonomous vehicle technology, how can we dispatch EAV taxis in better and smarter ways? Third, electric vehicles will be owned by more and more people in the coming future. How do we understand their charging behavior, so as to provide guidance to BEV use, charging infrastructure planning, and power grid capacity expansion? The following three sections will describe these problems in detail.

1.2.1. Feasibility of BEV Taxis

The first studied problem in this dissertation is the analysis of BEV taxi feasibility based on the travel activities of current gasoline taxis. BEV feasibility research typically discovers travel patterns from the travel data collected from vehicles for a period of time. The most frequently used indicator that infers a vehicle's suitability for BEVs is daily vehicle miles traveled, as seen in the BEV studies for Atlanta, USA (Pearre et al., 2011), Seattle, USA (Khan and Kockelman, 2012), Sydney, Australia (Greaves et al., 2014). For example, in

Atlanta the daily driving distance of 9% of sampled vehicles never exceeded 100 miles during data collection, as revealed by the driving data collected from 484 private gasoline cars over a year. This indicates that the daily driving needs of 9% of the sampled vehicles could be fulfilled by BEVs with a 100-mile range (Pearre et al., 2011). Other than DVMT, Dong and Lin (2014) quantified BEV feasibility as the probability that the ratio of travel distance between two charges to the battery range remains within a certain level. This research found out that about 10% of the sampled private car drivers in Seattle needed to make adjustment to less than 0.5% of travel days if they were comfortable with using up the range of 76 miles (i.e. representative of a Nissan Leaf 2012 model).

These studies focused on the BEV feasibility of private vehicles. Currently, there is little research into the BEV feasibility of taxis. Taxis have its own distinct characteristics in terms of long driving time and distance, shared use, and dwell patterns. A typical yellow taxi in New York City is operated by 3 drivers and travels 70,000 miles annually, and the average shift lasts for 9.5 hours (NYC TLC, 2014; NYC TLC, 2016). The data collected from taxis in other cities of China revealed long daily driving distances that are likely to exceed BEV range, such as in Beijing (Li et al., 2016), Shanghai (Luo et al., 2017), and Shenzhen (Nie, 2017). In terms of dwell patterns, Cai et al. (2014) said that approximately 80% of the studied taxis in Beijing had average parking time of at least 5 hours per day, and Bischoff et al. (2015) found that the taxis in Berlin, Germany were in favor of waiting for customers at airports for several hours (Bischoff et al., 2015). In only a few studies on the BEV feasibility of taxis, the BEV feasibility was examined from different perspectives, including environmental benefits (Yang et al., 2016), energy consumption (Zou et al., 2016), benefit-

to-cost ratio (Baek et al., 2016), daily driving distance (Chrysostomou et al., 2016), and electrification rate of vehicle miles traveled (Li et al., 2017).

This dissertation aims at examining the electric taxi feasibility from a different point of view based on taxis' spatial-temporal travel patterns. The specific research questions we want to answer are as follows.

(a) How to quantify the BEV feasibility of taxis?

(b) What are the travel patterns that make taxis more suitable for switching to BEVs?

In particular, taxis' spatial-temporal travel patterns in terms of driver-shift, travel demand, and dwelling are extracted from the taxi trip data.

(c) How to expand charging infrastructure coverage to improve BEV taxi feasibility?

1.2.2. EAV Taxi Dispatch

Electric and autonomous taxis have significant advantages over current taxis and ride-hailing taxis. Adopting EAVs for various kinds of mobility services have been discussed in a few literatures. Chen et al. (2016) simulated a fleet of shared EAVs that follow agent-based rules of driving and charging. It was found that one shared EAV is able to replace 3.7–6.8 private vehicles. Kang et al. (2017) designed an EAV sharing system and presented an optimization framework to determine the fleet size, charging infrastructure, vehicle assignment, and service fee. Jäger et al. (2017) focused on the agent-based simulation approach for a shared EAV on-demand mobility system, and found that a shared EAV fleet is able to provide both high service level and vehicle utilization. Iacobucci et al. (2018) modeled the operations of EAVs in the one-way car sharing service in Tokyo, Japan. This study revealed that the EAV car sharing can provide the same level of transport service as private cars, while the fleet size can reduce by 86%-90%.

The above studies all focused on the high operational efficiency of EAVs in the shared mobility services. The core of high efficiency is vehicle dispatch. Various methods have been used to study the vehicle dispatch problems of mobility services. The first and simplest one is the nearest vehicle dispatch method, that is, dispatching the vehicle that is geographically the nearest to a customer (Liao, 2003; Jung and Jayakrishnan, 2014; Hyland and Mahmassani, 2018). Dispatching the nearest vehicle is simple and it is often used as the base scenario to compare with other complex models. Second, queueing theory with the principle of first-come-first-served. The first customer that joins the waiting list will be picked up first (Zhang and Pavone, 2016; Jäger et al., 2017). Third, optimization models with different objectives were formulated to obtain optimal dispatch solutions. Qu et al. (2014) built a recommender system that provides taxi drivers with optimal driving route to maximize driver profits. Similarly, Sheppard et al. (2017) aimed at maximizing the profits of an EAV fleet, and Lu et al. (2018) wanted to minimize the total operating cost of a taxi fleet that serves advance reservations. Miao et al. (2016) focused on reducing taxi idle travel distance while maintaining service quality. Ma et al. (2017) designed an AV sharing and reservation model that optimally schedules AVs to serve the maximum number of customers. The AV taxi dispatch strategies in Hyland and Mahmassani (2018) were to minimize the total pickup distance when multiple requests enter the system. Machine learning is the fourth and emerging method to dispatch vehicles, especially reinforcement learning. Wen et al. (2017) proposed a reinforcement learning approach that adopts a deep Q-network to adaptively move idle vehicles to high-demand areas in a shared on-demand mobility system. Xu et al. (2018) also used reinforcement learning to solve a large-scale vehicle dispatch problem confronted by the ride-hailing company DiDi.

In this dissertation, we will study the potential of replacing current taxis with EAVs, especially the dispatch problems of EAV taxis. To be more specific, the following problems will be explored.

(a) What are the dispatch strategies for EAV taxis? A desired dispatch strategy should effectively reduce customer waiting time while keeping high operational efficiency of EAV taxis. In this research, we apply machine learning techniques to dispatch EAVs in a fast and efficient way.

(b) How to design a simulation framework for the operations of EAV taxis? The simulation framework should facilitate the evaluation of different dispatch models in terms of improving customer service and operational efficiency.

1.2.3. Charging Behavior of Personal BEV Drivers

The third problem is to model BEV drivers' charging behavior, such as the SOC when charging occurs, and choices of charging time and location (home, workplace, or public). Understanding the charging behavior will provide guidance to BEV use, charging infrastructure planning, and power grid capacity expansion.

In previous research, the charging decisions of electric vehicle drivers have been modeled using simple and deterministic rules. For example, charging only occurs at home (Kang and Recker, 2009; Darabi and Ferdowsi, 2011; Kongthong and Dechanupapritta, 2014), drivers decided to charge only if the benefit of charging is larger than the cost (Dong and Lin, 2012), and BEV taxi drivers would not charge vehicles until the SOC drops below a certain level (Hu et al., 2018; Yang et al., 2016). These models may hold true in the EV early adopter stage, but do not necessarily reflect realistic charging behaviors because it can be influenced by various factors.

Some studies took a step further and introduced random utility theory (RUT) to model BEV driver charging decisions under uncertain conditions and randomness. Daina et al. (2017) developed a joint random utility model of charging and activity-travel timing choices that considers various utilities across individuals. To incorporate heterogeneity among decision-makers, mixed logit choice models with random coefficients were developed to describe different charging behaviors, such as whether to charge at the end of each trip (Zoepf et al., 2013), fast charging station choices (Sun et al., 2016), and charge timing choices (Langbroek et al., 2017). RUT assumes that people are rational decision-makers and maximize utility relative to their choices. However, the rational decision-maker assumption has long been challenged by Kahneman and Tversky (1979), Durbach and Stewart (2012), and Ilin and Rogova (2017). People's irrational behaviors of travelling have been observed and studied, such as departure time choice (Mahmassani and Chang, 1986; Schwanen and Ettema, 2009) and route choice (Zhou et al., 2014).

Therefore, we need to consider the limited rationality when drivers make charging decisions. The cumulative prospect theory, proposed by Kahneman and Tversky (1979) and improved by Tversky and Kahneman (1992), describes the extent of decision-makers' attitudes and preference toward risk. CPT has found success in many transportation research fields to describe people's limited rationality and risk attitudes when making decisions., for example, route choice (Avineri and Bovy, 2008; de Luca and Di Pace, 2015; Gao et al., 2010; Wang and Xu, 2011; Xu et al., 2011; Yang and Jiang, 2014; Zhou et al., 2014), commuter departure time choice (Senbil and Kitamura, 2004; Schwanen and Ettema, 2009), public-transport users' mode choice at transfer stations (Ceder et al., 2013), use of the high-

occupancy-vehicle lane (Chow et al., 2010), classification of the risk attitude of travelers (Yang et al., 2015), and congestion pricing (Liu et al., 2010).

Charging behavior of BEV drivers is in accordance with the rationale of CPT. When people drive BEVs, there are no significant perceivable gains if the trip distance falls below the electric range, but if the distance unexpectedly exceeds the range and the driver is caught on the road or forced to detour to reach a public charger, the losses are perceivably large. In addition, BEV drivers tend to avoid range anxiety and recharge at high battery SOC.

The third problem that this dissertation studies is how to model the charging behavior of BEV drivers. This dissertation also examines the collective effects of nationwide BEV charging under a mature market by applying the CPT-based charging behavior model. To be more specific, the research questions that this dissertation will address are as follows.

(a) How to model BEV drivers' charging decisions allowing limited rationality? What are the impacts of drivers' risk attitudes and public charger network on charging behavior?

(b) What are the collective effects of charging behavior under the future BEV mass-market scenario? In particular, the characteristics of charging times and locations and the impacts on the power grid are of great interest.

(c) How to mitigate the impact of charging on the power grid through time-of-use electricity pricing scheme?

1.3. Dissertation Structure

This dissertation is organized as follows. Chapter 2 introduces the data used in this dissertation. The NYC taxi trip data were collected in the year of 2013. This chapter presents the data filtering methods, the way of estimating taxi trip distance, and the statistical facts of the NYC yellow taxi fleet. This dataset will be used for the studies in Chapter 3 and Chapter 4. The second dataset used for the research in Chapter 5 is 2017 National Household Travel

Survey data. The data schematic and statistical facts are presented. The Chapter 3 analyzes the feasibility to replace gasoline taxis with BEVs in New York City from the perspective of travel patterns. This chapter extracts ten variables from the trip data to represent the spatial-temporal travel patterns of taxis and proposes a model to quantify BEV feasibility. The charging infrastructure that supports large-scale adoption of BEV taxis is also studied in this chapter. Chapter 4 examines the second problem of this dissertation—the potential of replacing current taxis with EAVs. A simulation framework for the operations of EAV taxis is designed. An optimization-based model and a neural network-based model for EAV taxi dispatch are proposed. In addition, we compare the performance of current taxis and the EAV taxis that are dispatched by the neural network-based model. EAV taxis are able to improve operational efficiency and reduce fleet size. In Chapter 5, we propose a cumulative prospect theory based modeling framework to describe the charging behavior of drivers of personal BEV. Using the most updated 2017 National Household Travel Survey data, we build a BEV mass-market scenario. The collective effects of BEV charging under the mass-market scenario are explored. Finally, Chapter 6 summarizes the major findings and contributions of this dissertation, and discusses future research directions.

CHAPTER 2. DATA

2.1. New York City Taxi Trip Data

2.1.1. Data Description

New York City owns a large number of taxis, among which 13,587 were yellow taxis driven by 38,139 active drivers in 2015 (NYC TLC, 2016). Yellow taxis provide street hails and e-hails in the five NYC boroughs (i.e. Bronx, Brooklyn, Manhattan, Queens, and Staten Island) and the two airports (i.e. LaGuardia airport and John F. Kennedy international airport), as shown by Figure 2.1. Onboard GPS devices are implemented on the yellow taxis to track and record the timestamped trajectories during operation. NYC Taxi and Limousine Commission (TLC), the agency responsible for managing the city's taxicabs, published the taxi trip data since 2009.



Figure 2.1 *Location of NYC boroughs and airports (NYC TLC, 2014).*

The data used in this dissertation span the whole year of 2013 and was pre-processed by Donovan and Work (2016; 2017), who rendered the vehicle ID and driver ID pseudo

anonymous. The high resolution timestamped vehicle trajectories are not available. Instead, only records of occupied trips are available, which include when and where customers were picked up and then dropped off, travel distance, and travel time. Table 2.1 lists the data fields used in the dissertation.

Table 2.1 *Data fields used in the NYC yellow taxi trip data.*

Data field	Description
Medallion	The anonymous identification of each taxi.
Hack license	The anonymous identification of each driver.
Pickup datetime	The date and time when customers are picked up. The precision is up to seconds.
Dropoff datetime	The date and time when customers are dropped off. The precision is up to seconds.
Trip time in secs	The travel time measured by taximeter (second).
Trip distance	The trip distance measured by taximeter (mile).
Pickup longitude	The longitude of the location where customers are picked up.
Pickup latitude	The latitude of the location where customers are picked up.
Dropoff longitude	The longitude of the location where customers are dropped off.
Dropoff latitude	The latitude of the location where customers are dropped off.

2.1.2. Data Filtering

There are a considerable number of errors in the data, for example, trip length of 1,000 miles, zero travel time, and out-of-boundary GPS coordinates. Validity of the research results could suffer from these erroneous values, so the trip records that do not satisfy all the following three criteria are discarded.

- (a) Travel time is a positive value and does not exceed 3 hours.
- (b) Trip length is a positive value and does not exceed 100 miles.
- (c) The pick-up and drop-off GPS coordinates are within the range of 73.5° W to 74.25° W longitude, and 40.4° N and 41.1° N latitude.

As long distance trips have a significant impact on BEV feasibility, criterion (a) and (b) allow to keep long trips provided that the travel time and trip length are reasonable. The study area defined by criterion (c) is wider than the city boundary and covers three main airports—John F. Kennedy International (JFK), LaGuardia (LGA) and Newark Liberty International (EWR) that lie in the NYC suburb areas.

The whole-day data of a taxi is then removed if there is one or more erroneous trips, for these errors break up trip continuity and make DVMT estimation inaccurate. Trips that occurred on November 3rd, 2013 when the daylight saving time ended are also discarded because on that day clocks were tuned backward 1 hour to the standard time, making some trips chronologically disordered.

2.1.3. Unoccupied Trip Estimation

Although not captured in the data, unoccupied trips can be approximately reconstructed on the basis of two adjacent occupied trips, that is, an unoccupied trip starts from the drop-off location of the last occupied trip and ends at the pick-up location of the next occupied trip. With the GPS coordinates of the last drop-off and the next pick-up location, the empty trip's straight-line distance L is calculated as the Euclidean distance. Yang and Gonzales (2016) used Euclidean distance to represent real travel distance of unoccupied trips, which tends to result in underestimation. Zhan et al. (2016) estimated real distance by taking advantage of the road network of NYC, but this method is computationally heavy. In this dissertation, the actual distance D of unoccupied trips is estimated by Equation 2-1, that is the least-squares fitting result from the actual and straight-line travel distance of occupied trips. Here we assume that occupied and unoccupied trips share the same spatial relationship. With the help of taxi dispatch and e-hailing system drivers might know the location of the next customers and will drive along the shortest path.

$$D = 1.4413L + 0.1383 \quad (R^2 = 0.9485) \quad (2-1)$$

where

D is the actual travel distance (mile);

and L is the straight-line distance (mile).

Between two occupied trips, taxi drivers might cruise around, have a meal, take a short break, alter shifts, go back home, etc. Dwell time during an unoccupied trip is defined as the time intervals between the two consecutive occupied trips minus the travel time of the unoccupied trip. The travel speed of the unoccupied trip is calculated as the average of the speeds of the previous and the next occupied trips. The travel distance is estimated using Equation 2-1 and the straight-line distance between the drop off location of the previous trip and the pickup location of the next trip. The travel time of the unoccupied trip is calculated as the travel distance divided by the travel speed. Dwell location is assumed to be the drop-off location of the last occupied trip. As shown in Table 2.2, the estimated average unoccupied trip length in NYC is 1.72 miles, which is 41% lower than average occupied trip length. This number is similar to taxis in Nanjing, China, where both occupied and unoccupied trip information is available. In Yang et al. (2016), the average unoccupied trip length is 42% lower than the average occupied trip length. Note that taxis in both NYC and Nanjing are mainly street-hailed in current operations.

2.1.4. Summary Statistics of the Dataset

During the year of 2013, the entire dataset includes 14,144 yellow taxis, which were driven by 43,191 drivers, completed 173 million occupied trips with a total distance of 501 million miles. On average each taxi operated for 331 days in one year. After data filtering, there are 13,336 taxis with at least 70 days and an average of 306 days of trip data remaining.

The sampled fleet completed 149 million occupied trips with a total distance of 432 million miles, which represents 86% of the total occupied trips in 2013. Table 2.2 lists the summary statistics of the 13,336 taxis' travel patterns.

Table 2.2 *Summary of the travel patterns of the sampled taxi fleet.*

	Minimum	Mean	Maximum	Standard deviation
Occupied trip length (mile)	0.01	2.91	100	3.36
Occupied trip time (minute)	1	12.5	180	9.3
Unoccupied trip length (mile)	0	1.72	55	2.82
Number of occupied trips per day	1	36	122	14.5
DVMT (mile)	0.09	168	858	59
Number of dwells (>30min) per day	0	3.4	13	1.6

2.2. 2017 National Household Travel Survey Data

The Federal Highway Administration has been collecting travel behavior data of the U.S. residents in all 50 States and the District of Columbia through a random sampling approach since 1969. The 2017 National Household Travel Survey is the eighth and most recent survey (U.S. DOT, FHWA, 2017). The NHTS data is an inventory of travel behavior of a respondent during a travel day, including trips made by all modes of transportation, e.g. public transit, bicycle, personal vehicles, and ride-sharing, and for all purposes, e.g. work commute, recreation, and school. The NHTS is also the main source on how American people's travel behavior is linked to individual personal and household characteristics, socio-economic attributes, and vehicle ownership. There are four data files in the survey—TRIP, VEHICLE, PERSON, and HOUSEHOLD.

The TRIP file records all trips taken by each person in a household during a travel day. For each trip, the respondents report trip origin and destination, trip distance, mode of transportation, time of day of travel, day of week of travel, travel companions, etc. The

VEHICLE file of the 2017 NHTS consists of 242,160 passenger vehicles (i.e. cars, SUVs, vans, or pickup trucks) owned by the respondents. This dataset contains attributes of each vehicle, such as vehicle manufacturer, model, years owned, age, and odometer reading. The 2017 NHTS introduces a new field in the VEHICLE file—HFUEL to indicate the type of powertrain (gasoline engines, electric motors, or hybrid). HFUEL = 3 means that the vehicle is a BEV. The HOUSEHOLD data file contains information on the socio-economic characteristics of a respondent household, including family income, number of workers, housing type, neighborhood, area, etc. There are 129,696 households in the 2017 NHTS. For each individual household member, the PERSON data record the demographic characteristics of the person, e.g. gender, age, and driver status. The TRIP, VEHICLE, PERSON, and HOUSEHOLD data files can be linked to each other. Figure 2.2 illustrates the relationships between the four datasets.

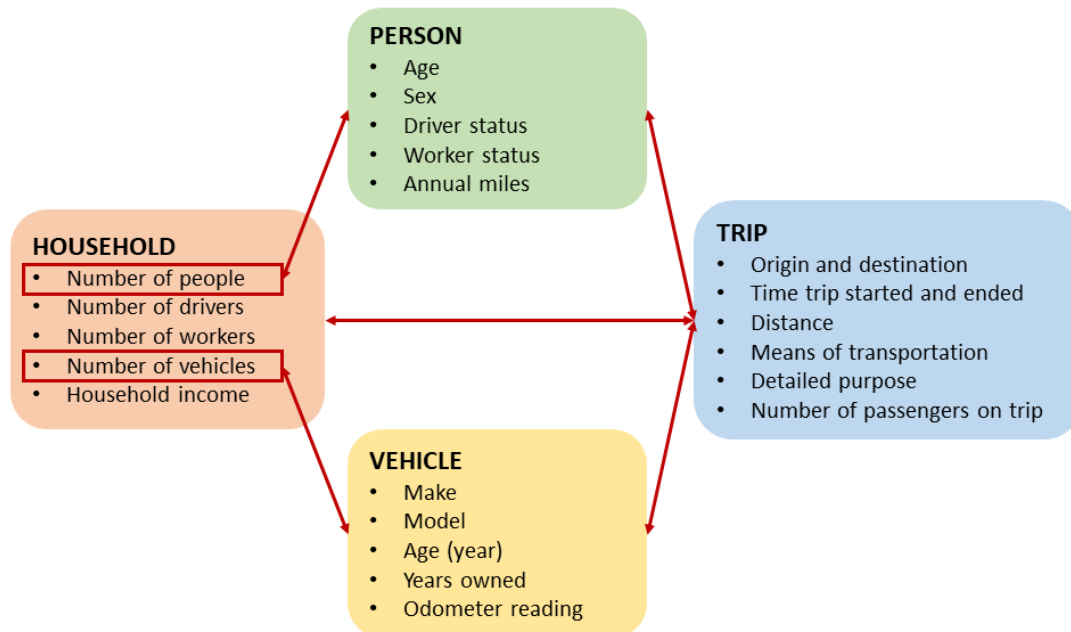


Figure 2.2 Schematic of the 2017 NHTS data.

CHAPTER 3. ANALYZING BATTERY ELECTRIC VEHICLE FEASIBILITY FROM TAXI TRAVEL PATTERNS: THE CASE STUDY OF NEW YORK CITY

3.1. Introduction

Vehicle electrification has been widely considered as a way to reduce the dependency of transportation sector on petroleum and reduce emissions of greenhouse gases and harmful air pollutants. In particular, since taxis usually drive in highly-populated areas, substituting the battery electric vehicles for conventional gasoline vehicles in the taxi fleet has the potential to improve urban air quality. BEVs are also attractive to taxi drivers, because of the lower electricity cost compared to gasoline and the less maintenance expenditure (Sathaye, 2014). As a result, cities around the world such as New York City, USA (NYC TLC, 2013), Berlin, Germany (Bischoff et al., 2015), Shenzhen, China (Tu et al., 2016) and Bogota, Colombia (Urban Foresight Limited, 2014) have been promoting electric taxis. In particular, New York City has a vision to replace one-third of taxi fleet with BEVs by 2020 (NYC TLC, 2013).

Nevertheless, BEV taxi deployment is impeded by several obstacles. Since taxis are usually continually operated by multiple shifts day and night, overnight charging at home might not be an option. Instead, within-day charging at public charging stations during taxi operation hours becomes necessary. However, in most cities the coverage of charging stations is still sparse. The profit-driven taxis would not want to wait for a long time to charge the batteries at the expense of losing customers. Frequent charging and depleting batteries may shorten the life of batteries (Barré et al., 2013), which is another concern over adopting BEVs in the taxi fleet. With the advances in battery technology, longer battery life, higher energy density and faster charging will relieve the range anxiety and reduce charging inconvenience. Ride-hailing services, coupled with self-driving cars, are expected to achieve

a more efficient dispatch system and may help promote large-scale BEV taxi deployment (Golson, 2017; Hawkins, 2017a).

This chapter analyzes the electric taxi feasibility based on the travel activities of current CGV taxis. BEV feasibility research typically extracts travel patterns from the travel data collected from vehicles for a period of time. Daily vehicle miles traveled is often used as one indicator to infer a vehicle's suitability for BEVs, as seen in Atlanta, USA (Pearre et al., 2011), Seattle, USA (Khan and Kockelman, 2012), Sydney, Australia (Greaves et al., 2014). For example, the driving data collected from 484 private CGVs over a year in Atlanta revealed that the daily driving needs of 9% of the sampled vehicles could be fulfilled by BEVs with a 100-mile range because their daily driving distance never exceeded 100 miles during the data collection period (Pearre et al., 2011). Other than DVMT, BEV feasibility is also quantified as the probability that the ratio of travel distance between two charges to the battery range remains within a certain level in Dong and Lin (2014). This research concluded that about 10% of the sampled private car drivers in Seattle needed to make adjustment to less than 0.5% of travel days if they were comfortable with using up the range of 76 miles (i.e. representative of a Nissan Leaf 2012 model).

The above-mentioned studies focused on the BEV feasibility of private vehicles. Taxis, on the other hand, have their own distinct characteristics in terms of shared use, long operational time, and dwell patterns. In New York City, a typical yellow taxi is assigned 3 drivers and travels 70,000 miles annually, and the average shift lasts for 9.5 hours (NYC TLC, 2014; NYC TLC, 2016). The data collected from taxis in Shanghai (Luo et al., 2017), Beijing (Li et al., 2016), and Shenzhen (Nie, 2017), China revealed long daily driving distances that are likely to exceed BEV range. In terms of dwell patterns, it is found that

approximately 80% of the studied taxis in Beijing had average parking time of at least 5 hours per day (Cai et al., 2014), and taxis in Berlin, Germany were in favor of waiting for customers at airports for several hours (Bischoff et al., 2015). BEV feasibility of taxis has been examined from different perspectives, including benefit-to-cost ratio (Baek et al., 2016), environmental benefits (Yang et al., 2016), energy consumption (Zou et al., 2016), daily driving distance (Chrysostomou et al., 2016), and electrification rate of vehicle miles traveled (Li et al., 2017). Different from previous studies, this research examines electric taxi feasibility based on taxis' spatial-temporal travel patterns in terms of driver-shift, travel demand and dwelling, as well as the impact of charging infrastructure coverage. The feasibility is quantified as the percentage of occupied trips that can be completed by BEVs during a year. The findings from the study can help taxi drivers make informed decisions to adopt BEVs and assist policy makers in allocating public resources in support of electric taxi deployment.

3.2. Methodology

3.2.1. Quantification of Electric Taxi Feasibility

This study quantifies a taxi's BEV feasibility as the percentage of occupied trips that can be completed by BEVs among all occupied trips during the year. Different from personal vehicles, taxis are usually driven day and night by multiple shifts. Thus, assuming that batteries can be fully charged overnight at home (Dong et al., 2014) is not practical for taxis. Instead, the proposed approach allows taxis to continuously operate for a one-year period and charge batteries during long dwell events. If taxis run out of electricity and have to resort to emergency charging, several subsequent occupied trips are probably missed.

Consider a fleet of electric taxis $I = \{1, 2, \dots, n\}$. Assume the batteries are fully charged at the beginning of the first occupied trip in 2013. For each taxi, travel distances of

both occupied and unoccupied trips can be estimated from the trip data. Accordingly, distance variables are defined as follows.

$od_{i(k)}$ Travel distance of taxi i 's k -th occupied trip (mile).

$ud_{i(k)}$ Travel distance of taxi i 's k -th unoccupied trip (mile), that is, the trip immediately after the k -th occupied trip.

BEV-associated parameters include electric range and electricity consumption rate. Tesla Model S (maximum 351-mile range) is among the candidates for NYC electric taxis in spite of its high price tag (NYC TLC, 2013). BEVs with shorter range, such as Tesla Model 3 (215-mile range) and Chevrolet Bolt (238-mile range), are more affordable—the price is about \$35,000 and \$30,000 after incentives, respectively (Chevrolet, 2017; Tesla, 2017). With technology advancement, it is predicted that BEVs will feature longer range at lower price in the near future (Ajanovic, 2015). Thus, this study considers the feasibility of using BEVs with ranges of 200 miles and 300 miles (i.e. $R_i = 200, 300, \forall i$) as taxis. Electricity consumption rate varies greatly due to different driving habits, traffic conditions and environmental factors. In this study a fixed consumption rate is assumed as 0.3 kW h/mile (i.e. $r_i = 0.3, \forall i$) (Plugin America, 2016).

R_i Electric range of taxi i (mile).

r_i Electricity consumption rate of taxi i (kW h/mile).

The charging decision depends on the dwell time, remaining electric range, distance to the nearest charging station, and so on. In this study, two types of charging are considered—dwell charging and emergency charging. For *dwell charging*, a taxi will charge if three conditions are satisfied. First, the dwell time is longer than 30 minutes. Currently almost all charging stations in NYC are installed with 20-kW AC Level 2 chargers. With

such chargers, the BEV's remaining range can increase by about 33 miles in half an hour. Taxi drivers might be reluctant to charge if dwell time is short. The 30-minute assumption was also used in other studies to define potential charging opportunities (e.g. Yi and Bauer, 2016, Li et al., 2017). Second, remaining electric range is below 50%. By studying the distribution of battery SOC before charging, Zou et al. (2016) found that around three quarters of BEV taxi drivers will not charge their cars until SOC drops below 50%. Thus, this research assumes taxi driver will consider charging if the SOC is below 50%. Third, the nearest charging station is within 0.5 miles. In the literature, the service radius of a charging station is assumed as 1 mile in (Cai et al., 2014) and 1.25 miles in (Li et al., 2017). This study assumes a smaller service radius of 0.5 miles considering taxi drivers' unwillingness to detour for charging and the heavy traffic in Manhattan. The related variables are defined below.

$dt_{i(k)}$ Dwell time between taxi i 's k -th and $(k+1)$ -th occupied trip (minute).

$ct_{i(k)}$ Charging time between taxi i 's k -th and $(k+1)$ -th occupied trip (minute).

st_i Setup time for charging of taxi i (minute). Assume to be 2 minutes, $\forall i$.

$R_{SOC,i(k)}$ Remaining electric range at the drop-off location of the k -th occupied trip (mile).

$cd_{i(k)}$ Straight-line distance from the drop-off location of taxi i 's k -th occupied trip to the nearest charging station (mile).

Therefore, the charging time is the dwell time minus a setup time for charging. The detour time is ignored for dwell charging since the charging station is within 0.5-mile radius.

$$ct_{i(k)} = \begin{cases} dt_{i(k)} - st_i, & dt_{i(k)} > 30, R_{SOC,i(k)} < 0.5R_i, cd_{i(k)} \leq 0.5 \\ 0, & otherwise \end{cases} \quad (3-1)$$

Multiple charging levels might be available at a charging station. This study considers 7-kW AC Level 1 chargers, 20-kW AC Level 2 chargers, and 50-kW DC fast chargers for the analysis, according to the SAE J1772 standard (SAE, 2016). Since taxi drivers generally prefer faster chargers, when multiple levels of chargers are available at a charging station the fastest charger will be chosen.

$P_{i(k)}$ The highest charging power at the nearest charging station from the drop-off location of taxi i 's k -th occupied trip (kW).

$R_{add,i(k)}$ Electric range increase by recharging at the k -th unoccupied trip (mile), which is determined by charging time and power, but will not exceed the battery capacity. Therefore,

$$R_{add,i(k)} = \min \left\{ R_i - R_{SOC,i(k)}, \frac{P_{i(k)} \cdot ct_{i(k)}}{r_i} \right\} \quad (3-2)$$

$R_{SOC,i(k)}$ is calculated based on the remaining range at the end of the previous trip, possible charging, and travel distance.

$$R_{SOC,i(k)} = R_{SOC,i(k-1)} + R_{add,i(k-1)} - ud_{i(k-1)} - od_{i(k)} \quad (3-3)$$

When $R_{SOC,i(k)}$ drops below 10% of range, taxi i needs *emergency charging* from the drop-off location of the k -th occupied trip, because it is very likely stranded in the next trip. If $R_{SOC,i(k)}$ becomes negative, taxi i has to resort to emergency charging from the drop-off of the $(k-1)$ -th occupied trip. That is, the taxi will not have accepted the k -th customer due to the insufficient range. During emergency charging, the taxi drives to the nearest charging station at the average speed calculated from the dataset—13 mph, and gets batteries fully charged (100% SOC). The detour distance ($dd_{i(k)}$ in miles) is estimated by Equation 2-1.

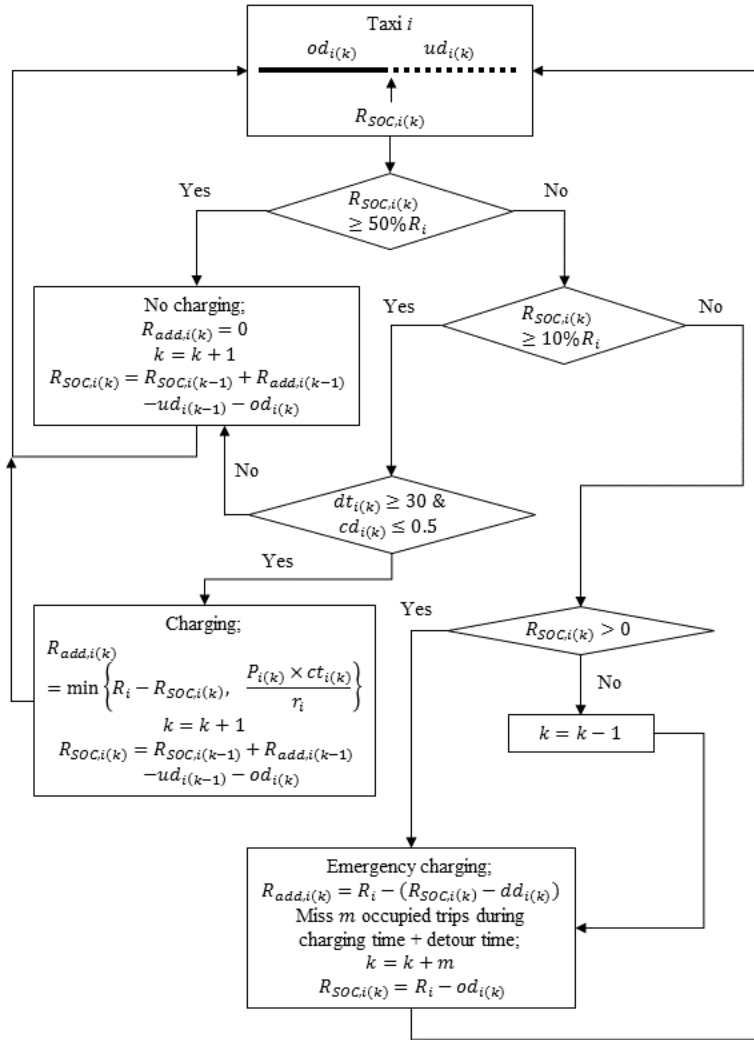


Figure 3.1 Flow diagram of the model of quantifying electric taxi BEV feasibility.

After charging is finished, the taxi will continue from the occupied trip that starts after the charging completion time. Since over 90% of taxi pick-ups and drop-offs occur in Manhattan (NYC TLC, 2014) that is only a small part of the studied area (see Figure 2.1), the trips from emergency charging stations to the next customer are short compared to BEV range (200 or 300 miles) and thus are ignored. As a consequence, several occupied trips probably are missed due to emergency charging, and the percentage of occupied trips during the year that can be electrified by public charging is used as the indicator of taxi i 's BEV feasibility (F_i). A taxi is regarded as BEV feasible if at least 99% of its occupied trips can be

completed by BEVs; otherwise the taxi is BEV infeasible. On average, a taxi works 306 days in the year and completes 36 occupied trips per working day. Therefore, a BEV-feasible taxi will miss only 2 ($\frac{306 \times 7 \times 36 \times 1\%}{365} = 2$) occupied trips per week.

The model of quantifying electric taxi BEV feasibility is illustrated in Figure 3.1.

3.2.2. Taxi Travel Patterns

Travel patterns represent how NYC yellow taxis are operated, and hence have some important implications on whether the CGV taxi can switch to a limited range BEV. For each taxi, we extract 10 variables from its travel activity data, to characterize its driving behavior in 3 aspects—driver-shift, travel demand, and dwelling. Table 3.1 describes these variables.

Table 3.1 *Ten taxi travel pattern variables extracted from data.*

Type	Variable	Description
Driver-shift related	X_1	Mean of the number of daily shifts.
	X_2	Mode of the number of daily shifts.
	X_3	Number of drivers assigned to the taxi in a year.
	X_4	Mean of the number of shifts per driver in a year.
Travel demand related	X_5	Mean of occupied trip length (mile).
	X_6	Mean of DVMT (mile).
	X_7	Mean of travel distance between two charging opportunities (mile).
Dwelling related	X_8	Mean of the number of daily dwells.
	X_9	Mean of dwell length (minute).
	X_{10}	Percentage of dwells occurred in Manhattan (%).

The first four variables are driver-shift related, explaining the features of shifts and drivers assigned to a taxi. Taxis are driven by one or more shifts during a day. Intuitively, more daily shifts are likely associated with longer hours of operation and longer travel distance, which might make it less suitable to switch to a BEV. In addition, a taxi might be assigned to different drivers over a year, denoted by X_3 . Some taxis have one or two fixed drivers during the entire year, while others change drivers frequently. The other driver-shift

related variable (X_4) is calculated based on Equation 3-4, which indicates, for a certain taxi, the average number of shifts that a driver is assigned to the taxi in a year. X_3 and X_4 reveal whether a taxi has stable driver assignment.

$$X_4 = \frac{N \times X_1}{X_3} \quad (3-4)$$

where

N is the number of working days.

In terms of travel demand, the variables of interest include the average length of occupied trips (X_5) for each taxi and the daily vehicle miles traveled (X_6). A taxi that often drives a lot might not be suitable for BEVs. To account for limited coverage of public charging network in the city, the travel distance between two consecutive charging opportunities (X_7) is calculated based on the charging station locations. When a taxi dwells for more than 30 minutes and the nearest charging station is within 0.5 miles, the taxi has an opportunity to charge.

Furthermore, dwell patterns are important for electric taxis, because taking advantage of parking time to charge batteries causes minimal inconvenience. The temporal characteristics of dwell events are captured by the average number of daily dwells (X_8) and the average dwell length (X_9), which collectively determine the possible charging time during a day. The spatial characteristics of dwell events are represented by the percentage of dwells occurred in Manhattan (X_{10}), as this borough has better charging infrastructure coverage and taxis are more likely to find a charger.

3.2.3. Expansion of Charging Infrastructure

As of December 22, 2016, there were 280 public charging stations in use in New York City, among which 223 (80%) are located in Manhattan, 2 in JFK airport and 4 in LGA

airport (U.S. DOE, 2016). Detailed information associated with these stations such as address, number of chargers, levels of chargers is available through (U.S. DOE, 2016). Almost all the charging stations are installed with Level 2 chargers. Figure 3.2 illustrates the station locations, with the corresponding service area covered (i.e. a buffer of 0.5-mile radius). It is seen that Manhattan has extensive charging station coverage, while very few chargers are located at other boroughs.

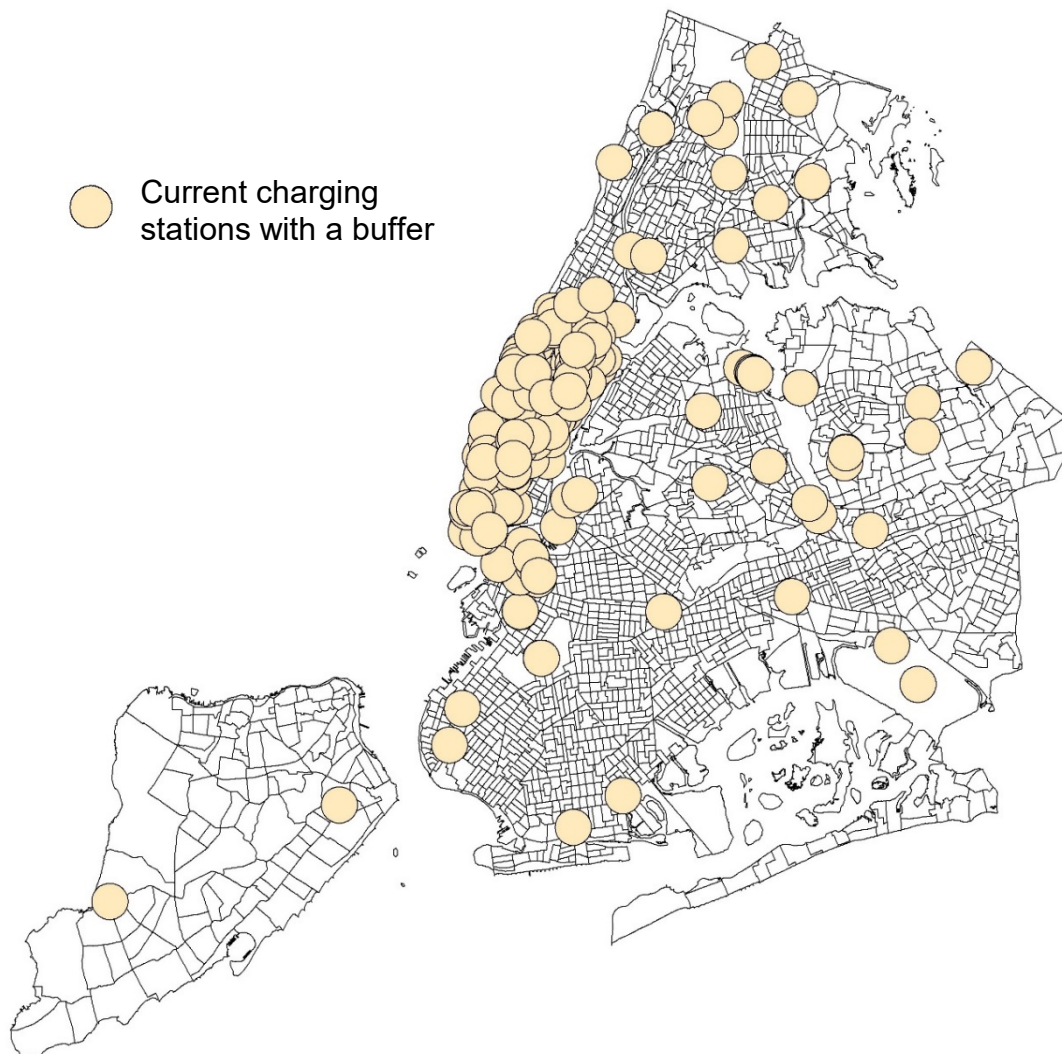


Figure 3.2 *Current public charging network in NYC, with a buffer of 0.5-mile radius.*

The current charging infrastructure in NYC includes public accessible stations (about 54%) and private business stations, such as Tesla superchargers (about 40%) and car-dealership chargers for their customers (about 6%). BEV taxis can use public accessible stations for charging and pay electricity and usage fees. The private business stations might be incompatible with or inaccessible to BEV taxis. These issues might be mitigated through installing converters, pricing, etc. For example, Tesla has introduced the Tesla-to-J1772 adapter to allow non-Tesla electric vehicles, e.g. BMW i3 or Nissan Leaf, to charge at Tesla's supercharger stations (Lambert, 2017). As seen in Figure 3.2, the current charging infrastructure provides good coverage in Manhattan. In practice, additional grid capacity is usually reserved to serve potential peak load and future expansion at existing charging station locations (Xi et al., 2013). Therefore, we use the current charging station locations as the base case charger network coverage, acknowledging that capacity expansion or accessibility barriers need to address at some of the locations.

Insufficient charging infrastructure is one of the hindrances to electric vehicle adoption. New York City plans to expand the charger network to boost BEV taxis because the current charging stations are nearly impossible to meet the charging demand of a large-scale fleet of BEV taxis (NYC TLC, 2013). Thus, in this chapter, a scenario of expanded charger network is considered for BEV taxi feasibility analysis. Various approaches have been proposed in the literature to site charging facilities (e.g. He et al. 2015, Yang et al. 2017, Shahraki et al. 2015). This study considers the centers of the census tracts as potential charging station locations. For each census tract of NYC, a spatial joining is conducted to count the number of dwell locations where taxis cannot reach a charger within 0.5 mile based on the existing charger network. New charging stations are added in the census tracts where

taxis frequently dwell. Since taxis prefer waiting for customers at airports, new charging stations are placed at several parking lots within the JFK and LGA airport census tracts to cover as many dwell locations as possible.

3.3. Results

3.3.1. Expanded Charging Network

New charging stations are sited at the census tracts where taxis frequently dwell. Figure 3.3 shows the distributions of daily dwell events without a nearby charging station.

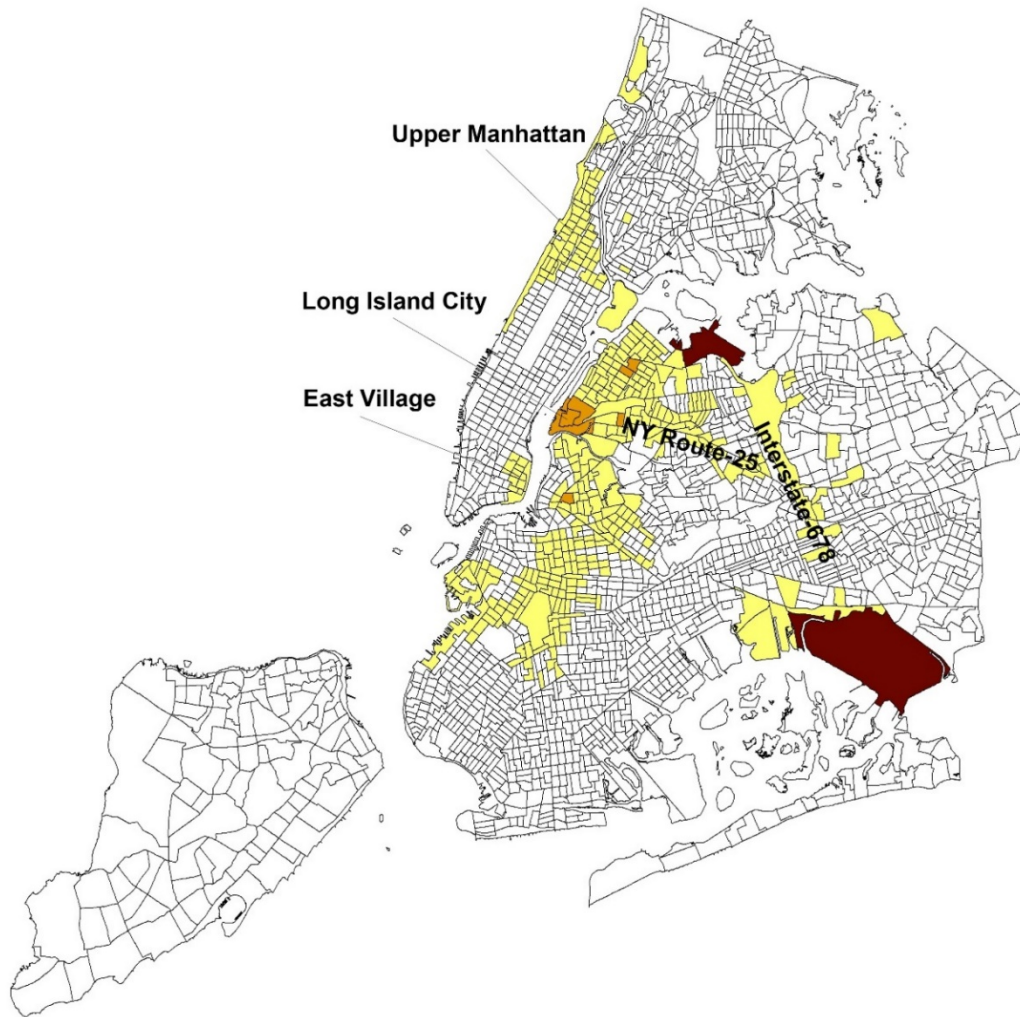


Figure 3.3 *Distributions of daily dwells without charging opportunities.*

JKF and LGA airport have averagely 773 and 122 dwells without charger per day, respectively, constituting the top 2 places where taxis have large unmet charging needs. Although the trips to EWR airport are considered in this study, no additional charging station is added, as EWR is in the state of New Jersey. Another area with relatively large unmet charging demand (i.e. 50~100 dwells per day) is Long Island City, which is the westernmost neighborhood of Queens and adjacent to midtown Manhattan. This is likely where drivers change shifts (Grynbaum, 2011). The other census tracts with considerable unmet charging demand (i.e. 5~50 dwell per day) are mainly distributed at Upper Manhattan, East Village of Manhattan, Northwest Queens adjacent to Manhattan, Middle North Brooklyn, along Interstate-678 connecting the two airports, along New York Route-25 connecting Manhattan and Interstate-678, and the areas near JFK airport.

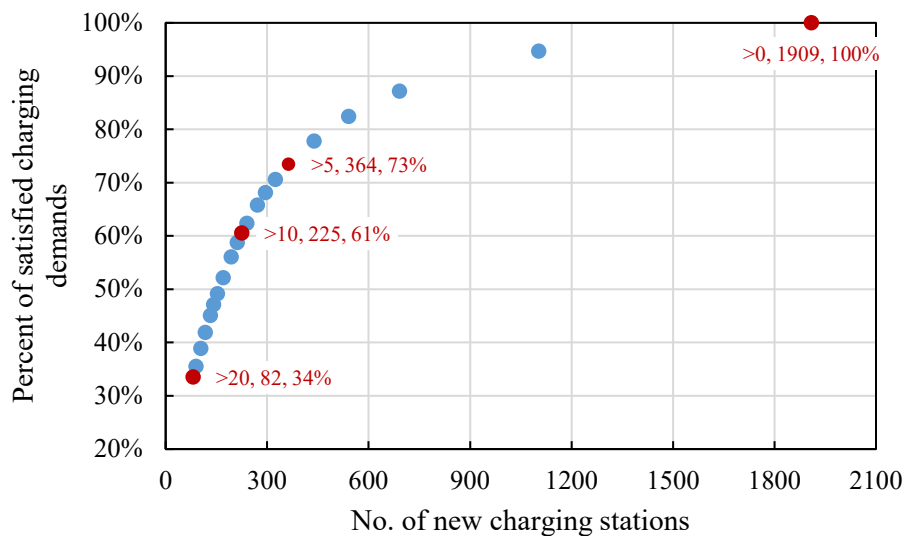


Figure 3.4 Relationship between number of new charging stations and percent of satisfied charging demands.

A new charging station is placed at the geometric center of a non-airport census tract polygon that has more than 5 dwells without charging opportunities per day. 364 census tracts, colored with yellow and orange in Figure 3.3, satisfy the condition and accommodate

73% of charging demands in non-airport census tracts. Figure 3.4 plots the number of new charging stations and the percentage of satisfied charging demands with different selection thresholds, from >20 to >0 dwells. With lower threshold and more charging stations, more charging demands can be covered, however, the marginal benefit decreases after >5 dwells.

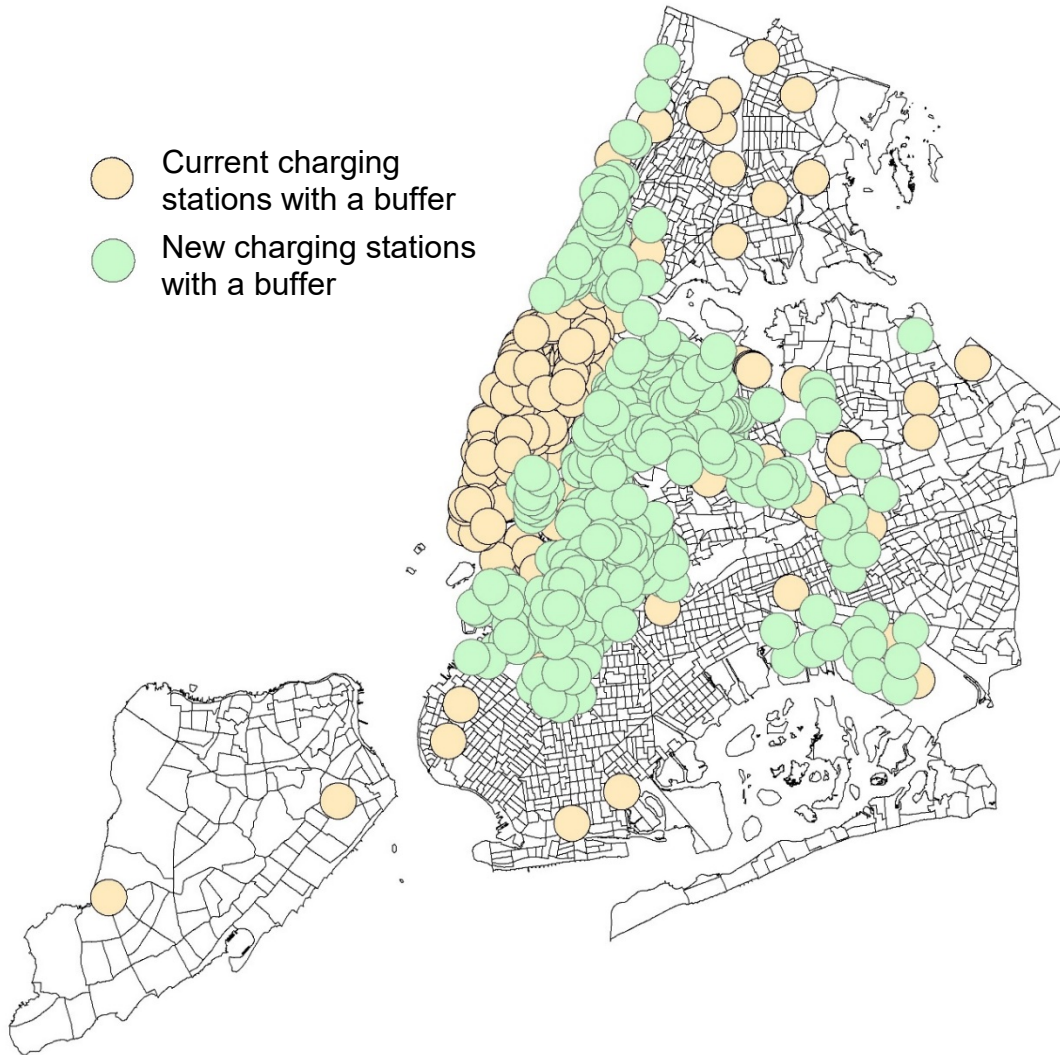


Figure 3.5 *Expanded public charging network in NYC, with a buffer of 0.5-mile radius.*

The airports, however, cover a larger area and have more available parking spaces for building charging stations. Thus, we select 2 parking lots at LGA airport and 6 parking lots at

JFK airport to add charging stations, in order to cover as many dwell locations as possible. In total, 372 new stations are added in the expanded charging network. With the additional charging stations, the entire public charging infrastructure in NYC is displayed in Figure 3.5.

3.3.2. BEV Taxi Feasibility

The feasibility of replacing CGV taxis in New York City with BEVs with a range of 200 miles and 300 miles is examined. If a taxi can complete at least 99% of the occupied trips using a BEV, it is considered BEV feasible. Some taxis might achieve the feasibility with 200-mile range BEVs; while others might require a battery range of 300 miles. If 300-mile range still cannot complete a majority of occupied trips for some taxis, they are considered as BEV infeasible. Therefore, all taxis are categorized into 3 groups—BEV 200-feasible, BEV 300-feasible, and BEV infeasible.

Figure 3.6 compares the electric taxi feasibility by group for current and expanded charging infrastructure in New York City. The existing 280 public charging stations are far from adequate to serve electric taxis. Only 1.4% of taxis are BEV 200-feasible and 5.4% of taxis are BEV 300-feasible, while 93.1% of the fleet cannot complete 99% of occupied trips using a BEV-300. However, when the number of charging stations is expanded to 652, taxis have more charging opportunities and thus fewer occupied trips will be missed. About half of the infeasible taxis become BEV feasible. In particular, BEV 300-feasible group increases dramatically to 5,667 taxis (or 42.5% of the fleet), and the share of BEV 200-feasible taxis increases to 8.0%.

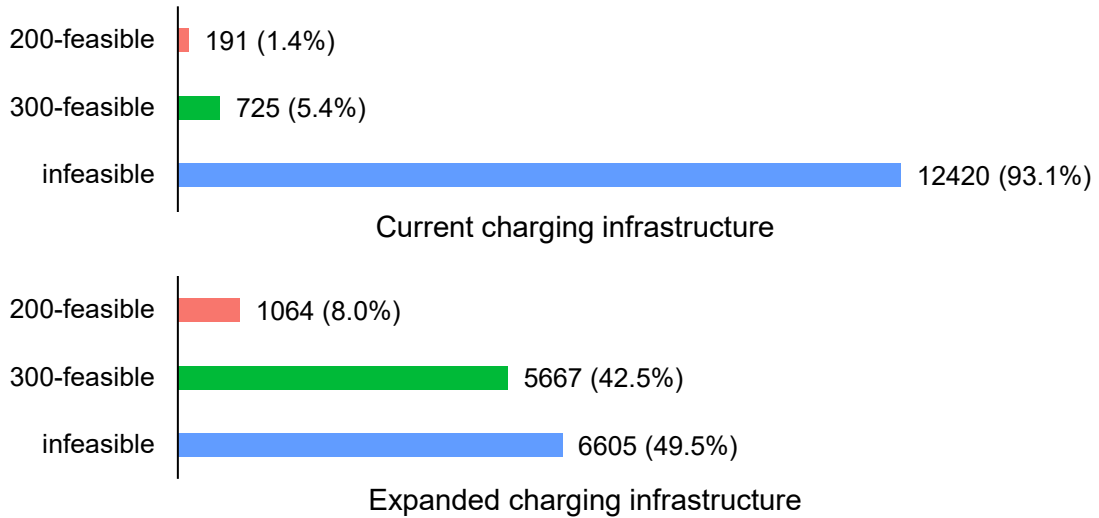
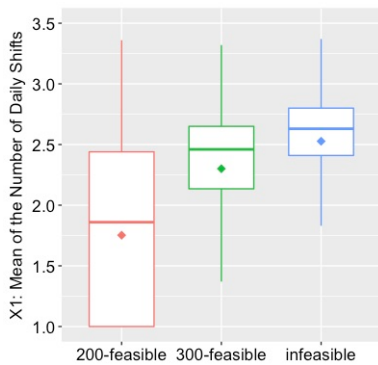


Figure 3.6 *Electric taxi feasibility by group for current and future charging infrastructure.*

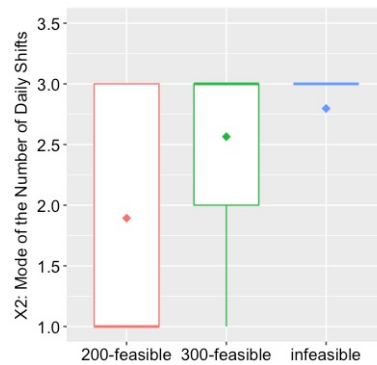
3.3.3. Impacts of Travel Patterns on BEV Taxi Feasibility

Considering the expanded charging infrastructure, the travel patterns of the three groups exhibit distinct characteristics. Figure 3.7 shows the boxplots by group of the 4 driver-shift related variables after removing outliers. The group means are marked by the square points. Figure 3.7(a) and Figure 3.7(b) show that fewer daily shifts are associated with higher BEV feasibility, probably because these taxis are driven fewer hours and are more likely to have long dwell time between shifts for charging. Specifically, we have found that (1) BEV 200-feasible taxis have the lowest average number of daily shifts, with the mean of 1.8 shifts per day; while BEV infeasible taxis, as expected, are driven intensively, with the mean of 2.5 shifts per day; (2) BEV 200-feasible group also has the largest variation in daily shifts, as the taxis with 1 shift per day generally fall in this category; (3) the distributions of the mode of the number of daily shifts confirm that BEV 200-feasible taxis have fewer shifts, and most BEV 200-feasible taxis operate 1~2 shifts per day; and (4) most BEV 300-feasible and BEV infeasible taxis have 3 shifts per day. Other than shifts, we also examine the

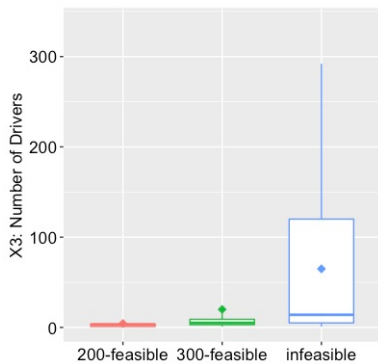
number of drivers assigned to a taxi and the yearly shifts a driver conducts to explore the relationship between drivers and taxis. As shown in Figure 3.7(c), BEV feasible taxis tend to have fewer drivers, that is, more stable driver assignment over a year. By contrast, BEV infeasible taxis could have as many as 329 different drivers during the year. The distributions of the average number of shifts per driver, as shown in Figure 3.7(d), also reveal that BEV feasible taxis tend to have more stable driver assignment. The median of the yearly number of shifts per driver for the BEV infeasible group is 54, much lower than the BEV feasible groups (i.e. 195 for BEV 200-feasible and 141 for BEV 300-feasible). In short, the driver-shift patterns imply that fewer shifts and less frequently change of drivers are favorable to BEV use.



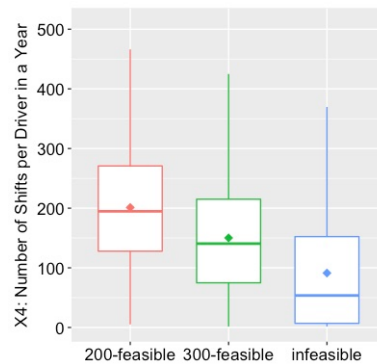
(a) mean number of daily shifts



(b) mode of number of daily shifts



(c) number of drivers



(d) number of shifts per driver

Figure 3.7 *Boxplots by group of driver-shift related variables.*

Figure 3.8 compare the distributions of the travel demand related variables for different BEV feasibility groups. We concern about whether the CGV taxi travel needs can be met by a BEV-200 or BEV-300. First, in terms of the average occupied trip length (Figure 3.8(a)), there is no significant difference between groups. One possible reason is that over 90% of occupied trips occurred in Manhattan (NYC TLC, 2014) and these trips tend to have similar length. The average of DVMT, however, have a direct impact on BEV feasibility as shown in Figure 3.8(b). Taxis with shorter DVMT are most suitable for BEVs. The group means are 111 miles, 157 miles and 184 miles for BEV 200-feasible, BEV 300-feasible and BEV infeasible group, respectively. Since DVMT indicate demand for BEV range, taxis that travel fewer miles a day are more likely to adopt BEVs. A few taxis with average DVMT of over 200 miles are BEV 200-feasible, which is possibly because they have proper within-day charging opportunities. On the other hand, the average DVMT of the majority of BEV infeasible taxis are less than 200 miles. Neither BEVs-200 nor BEVs-300 can complete 99% of the occupied trips of these taxis. This is due to the day-to-day variations in DVMTs and the lack of charging opportunities. Mean travel distances between two charging opportunities also show significant differences among groups (seen in Figure 3.8(c)). On average, a BEV 200-feasible taxi will dwell near a charging station after traveling 38 miles. BEV 300-feasible and BEV infeasible taxis, on average, need to drive 48 miles and 58 miles, respectively, to find a charging opportunity. The likelihood of coming across charging opportunities depends on where and how often the driver dwells for more than 30 minutes. If a taxi usually dwells outside the charging station coverage areas, its chance of switching to a BEV would become lower.

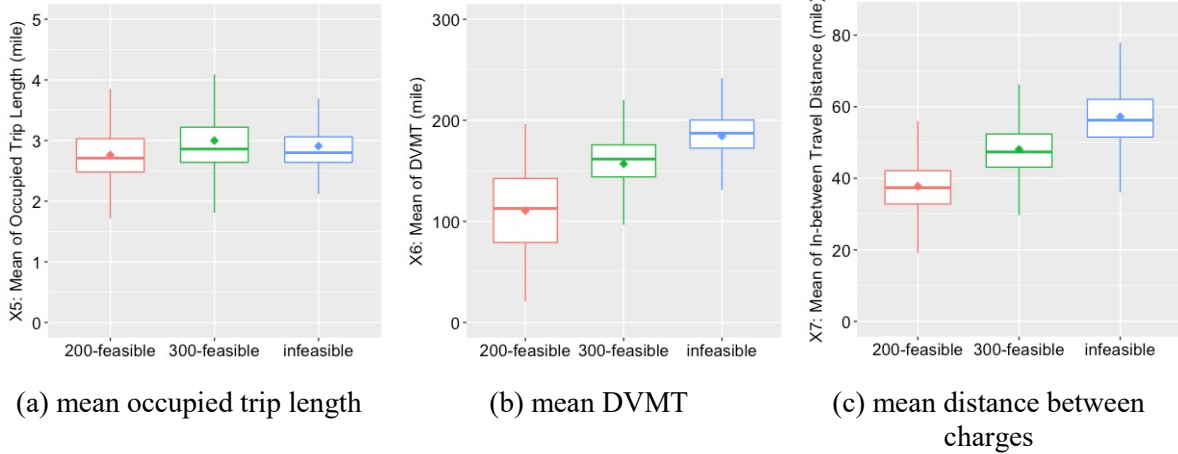


Figure 3.8 *Boxplots by group of travel demand related variables.*

The spatial-temporal dwell patterns are associated with where and when taxis can potentially charge battery. From the boxplots of the mean of daily number of dwells in Figure 3.9(a), it is found that BEV 300-feasible and BEV infeasible taxis share similar mean values, that is, around 3.2 dwells per day, but a slightly larger variance is observed in the BEV 300-feasible group. BEV 200-feasible taxis have even larger variance, peaking at 6 times of dwelling per day, with slightly lower mean and median than the other two groups. The distributions of dwell lengths are shown in Figure 3.9(b). BEV 200-feasible taxis have significantly longer dwell durations, with the group mean of 356 minutes. BEV infeasible taxis dwell for the shortest time period (209 minutes on average), indicating the time can be used for charging is limited. The spatial dwell feature is represented by the percentage of dwells that occurred in Manhattan, as this borough has wider charger coverage. The results in Figure 3.9(c) show that BEV 200-feasible taxis are more likely to dwell in Manhattan (92.7% on average), and correspondingly these taxis have more access to charging facilities.

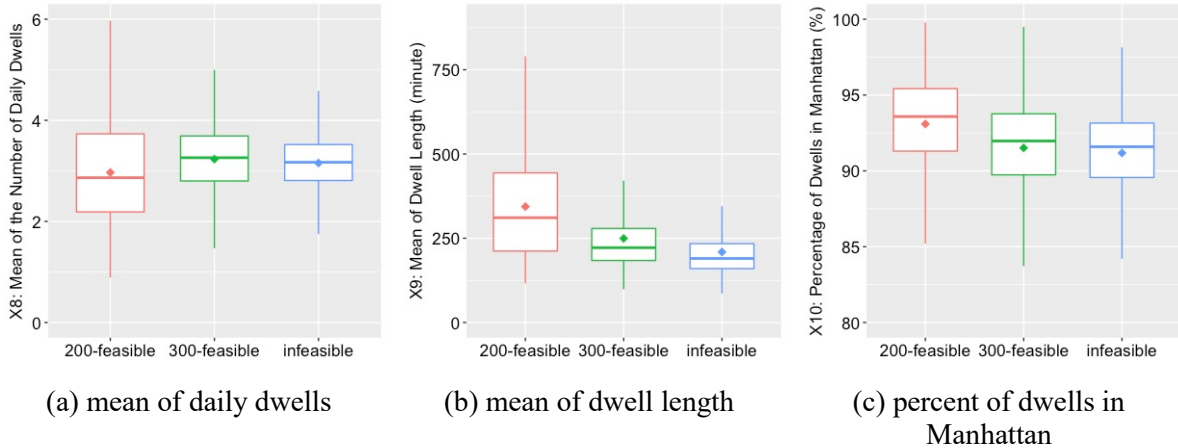


Figure 3.9 *Boxplots by group of dwelling related variables.*

In summary, from the above analysis, it can be concluded that a taxi with such travel patterns are more suitable to switch to a BEV—fewer daily shifts, fewer different drivers, more shifts per driver conducts in a year, shorter daily driving distance, shorter travel distance between charges, less number of daily dwells but longer dwelling time, and a higher possibility of dwelling in Manhattan.

3.3.4. Factors Influencing the Change of BEV Feasibility

With the current 280 charging stations, 12,420 taxis are labeled as BEV infeasible. If the additional 372 charging stations are built, 44% of the currently BEV infeasible taxis will become BEV 300-feasible and 3% will become BEV 200-feasible, while the remaining 53% will still be BEV infeasible. To examine how travel patterns influence the change from currently BEV infeasible to BEV feasible (either BEV 200-feasible or BEV 300-feasible) after the expansion of charging network, classification models that use the 10 travel pattern variables as input are developed. Five classification models, including logistics regression, linear discriminant analysis, quadratic discriminant analysis, K-nearest neighbors, Bayes classification and support vector machine, are trained by 70% of the dataset and tested by the rest 30% of the dataset. The training and testing accuracies are shown in Table 3.2.

Table 3.2 *Training and testing accuracy of classification models.*

Classification model	Training accuracy	Testing accuracy
Logistic regression	82.01%	81.87%
Linear discriminant analysis	81.72%	81.65%
Quadratic discriminant analysis	79.51%	79.23%
K-nearest neighbors	77.66%	77.09%
Bayes classification	76.20%	76.12%
Support vector machine (linear kernel)	71.98%	72.05%

Since logistic regression has the highest training accuracy (82.01%) and testing accuracy (81.87%), it is selected to classify BEV feasible taxis and BEV infeasible taxis after the expansion of the charging network. The model form is as follows:

$$\log\left(\frac{p}{1-p}\right) = b_0 + b_1X_1 + b_2X_2 + \dots + b_{10}X_{10} \quad (3-5)$$

where p is the probability that a currently BEV infeasible taxi will become BEV feasible when charging network is expanded, and b 's are model coefficients. The estimated model parameters are given in Table 3.3. The Cox & Snell R-square and the Nagelkerke R-square of the model is 0.443 and 0.591, respectively, suggesting a moderate fit. The Wald chi-square test is applied to each estimated coefficient. The significance (smaller than 0.5) associated with the Wald statistics shows that all the coefficients are significantly different from zero, indicating all the 10 variables representing taxi travel patterns have a significant contribution to discriminating BEV feasible and infeasible taxis. Therefore, the logistic regression model can predict whether a currently BEV infeasible taxi will become feasible when charging infrastructure is expanded.

The odds-ratios in Table 3.3 are exponents of the model coefficients and indicate the impacts of one unit change in the taxi travel pattern variables on the odds of becoming BEV feasible $\left(\frac{p}{1-p}\right)$. The odds-ratio of X_7 is smaller than that of X_6 , indicating that the BEV

feasibility odds are more sensitive to the average travel distance between charges than to the average DVMT. Therefore, improving charger network coverage and reducing the travel distance between charges might be more effective in increasing BEV feasibility than adopting longer range BEVs. In terms of dwell patterns, the currently BEV infeasible taxis are 1.532 times and 1.082 times more likely to become BEV feasible by increasing the average number of daily dwells by 1 (i.e. X_8) and increasing the percentage of dwells in Manhattan by 1% (i.e. X_{10}), respectively.

Table 3.3 *Estimated parameters of the logistic regression model.*

Variable	Coefficient	Standard deviation	Wald chi-square test statistics	Significance	Odds-ratio
X_1 : Mean of the number of daily shifts	1.388	0.176	61.963	0.000	4.009
X_2 : Mode of the number of daily shifts	-0.076	0.092	0.675	0.411	0.927
X_3 : Number of drivers	-0.007	0.001	102.783	0.000	0.993
X_4 : Number of shifts per driver in a year	0.003	0.000	64.656	0.000	1.003
X_5 : Mean of occupied trip length	0.141	0.057	6.101	0.014	1.152
X_6 : Mean of DVMT	-0.055	0.004	242.337	0.000	0.947
X_7 : Mean of travel distance between charges	-0.145	0.010	215.517	0.000	0.865
X_8 : Mean of the number of daily dwells	0.427	0.167	6.520	0.011	1.532
X_9 : Mean of dwell length	0.003	0.001	12.021	0.001	1.003
X_{10} : Percentage of dwells occurred in Manhattan	0.079	0.012	42.795	0.000	1.082
Constant	3.815	1.509	—	—	45.365

3.4. Conclusions and Discussions

This chapter examines the feasibility of substituting the gasoline-powered yellow taxis in New York City with BEVs from the perspective of the taxi travel patterns. Ten variables are extracted from a whole year taxi trip dataset to characterize the taxi spatial-temporal driving patterns in terms of driver-shift, travel demand and dwelling. An activity-based approach is proposed to quantify the BEV taxi feasibility as the percentage of occupied trips that can be electrified. It is found that the existing charging network in New York City is far from sufficient to satisfy the charging demand of a large-scale electric taxi fleet—only 8% of yellow taxis can complete 99% or more of the occupied trips if switching to BEVs with a range of 200 miles or 300 miles. 372 new charging stations are sited at census tracts of New York City where taxis frequently dwell without available chargers. With the expanded charging network, about half of the currently BEV infeasible taxis may become suitable for a BEV-200 or a BEV-300. In particular, taxis with certain travel patterns are more suitable for BEVs, including fewer daily shifts, fewer assigned drivers, shorter DVMT, shorter travel distance between charging opportunities, less number of dwells but longer dwelling time, and a higher possibility of dwelling in Manhattan.

There are four main caveats in this study. First, the travel distance, travel time and speed of unoccupied trips are estimated based on adjacent occupied trips, as the actual unoccupied trip information is not available. With street-hailing operations, unoccupied trips may have more detours than occupied trips. However, considering a future scenario when taxis are replaced by BEVs and assisted by the increasingly popular taxi dispatch and e-hailing systems. Taxi drivers will know the location of next customers and drive along the shortest path. As a result, the unnecessary detours of unoccupied trips will be significantly reduced. Second, during emergency charging, the taxi might not have enough electricity to

drive to the nearest charging station. After charging is completed, the travel distance from emergency charging station to the next customer is also ignored in the simulation. Since over 90% of taxi pick-ups and drop-offs occur in Manhattan (NYC TLC, 2014), these detour trips are short and have negligible impacts on the BEV taxi feasibility analysis. Third, the study assumes that BEV taxis will serve the same occupied trips as the CGV taxis, except for missing trips due to insufficient range. In practice, the BEV taxi fleet can satisfy the same customer demand without following their original routes. Since the results show how taxis' spatial-temporal travel patterns, in terms of driver-shift, travel demand and dwelling etc., affect electric taxi feasibility, BEV taxis could follow trajectories different from CGV taxis to achieve the same electrification target, as long as the collective travel patterns remain the same. In addition, optimizing the dispatch of taxis to customers can reduce the empty miles and may further improve the BEV feasibility. The taxi dispatching problem is, however, beyond the scope of the present research. Fourth, charging congestion is not considered. Given the limited public charging resources in New York City, BEV taxis might have to wait for charging at the expense of missing more occupied trips if the charging station is fully occupied. In addition, since usage rates of charging facilities vary over time, charger congestion could be worse during peak hours. Therefore, charging congestion might decrease taxis' BEV feasibility. On the other hand, installing fast chargers at popular locations might alleviate charging congestion. By ignoring the charging congestion issue, we implicitly assume the market efficiency of charging location owners in adding charger capacity or implementing smart grid technologies in response to charging demand.

CHAPTER 4. ELECTRIC AUTONOMOUS TAXI DISPATCHING: MODELING AND SIMULATION

4.1. Introduction

Taxis are usually pioneers to adopt emerging vehicle technologies. Electric vehicles have entered the taxi market in major cities around the globe (Kim et al, 2017; NYC TLC, 2013; Tian et al., 2016; Zou et al., 2016). Ride-hailing companies, such as Uber and Lyft, have started testing autonomous vehicle taxis on public roads in the U.S. (Hawkins, 2017a, b). Waymo, an AV technology development company, combines the two vehicle technologies together and is using a fleet of electric and autonomous vehicles for its ride-hailing taxi service in Arizona (Hawkins, 2018). There is a trend that more EAVs will hit road for future mobility services.

EAV taxis have significant advantages over current taxis and ride-hailing taxis. Current taxis usually cruise on the streets and search for customers by chance. Ride-hailing apps make the locations of customers available to drivers, but the customers may not be served by the best-matching taxis. A customer request is sent to multiple nearby drivers. The customer will be picked up by the fastest driver to accept the request, but the pickup distance might not be the shortest. By contrast, EAV taxis can be controlled by a central system that has access to customer information, e.g. locations, trip distance, and waiting time, and taxi information, e.g. locations, status, and battery state-of-charge. EAV taxis can operate in a collaborative manner based on the customer and taxi information and potentially improve operational efficiency and customer satisfaction. EAV taxis can work without taking a rest. The fleet size of EAV taxis can be dynamic based on customers' demand, while the number of working current taxis or ride-hailing taxis is less controllable. EAV taxis reduce tailpipe

emissions and save fuel expenditures. Charging can be better coordinated through vehicle-to-vehicle and vehicle-to-infrastructure communications so as to alleviate range anxiety.

Adopting EAVs for different kinds of mobility services have been discussed in a few previous works. Chen et al. (2016) simulated a fleet of shared EAVs that follow agent-based rules of driving and charging. They found that one shared EAV is able to replace 3.7–6.8 private vehicles. Kang et al. (2017) designed an EAV sharing system and presented an optimization framework to determine the fleet size, charging infrastructure, vehicle assignment, and service fee. Jäger et al. (2017) focused on the agent-based simulation approach for a shared EAV on-demand mobility system. It was found that a shared EAV fleet is able to provide both high service level and vehicle utilization. Iacobucci et al. (2018) modeled the operations of EAVs in the one-way car sharing service in Tokyo, Japan. The results showed that the EAV car sharing can provide the same level of transport service as private cars, while the fleet size can reduce by 86%-90%. These studies all focused on the high operational efficiency of EAVs in the shared mobility services, and the core of high efficiency is vehicle dispatch.

The vehicle dispatch problems in mobility services have been studied by various methods. The first and simplest one is the nearest vehicle dispatch method—dispatching the vehicle that is geographically the nearest to a customer. This method was adopted by Liao (2003), Jung and Jayakrishnan (2014), and Hyland and Mahmassani (2018). Although dispatching the nearest vehicle is simple, it can be used as the base scenario to compare with other complex models. Second, queueing theory with the principle of first-come-first-served. The first customer that joins the waiting list will be picked up first, as seen in Zhang and Pavone (2016), and Jäger et al. (2017). Third, optimization models were formulated to solve

the dispatch problems with different objectives. Qu et al. (2014) built a recommender system that provides taxi drivers with optimal driving route to maximize driver profits. Similarly, Sheppard et al. (2017) aimed at maximizing the profits of an EAV fleet, and Lu et al. (2018) aimed at minimizing the total operating cost of a taxi fleet that serves advance reservations. Miao et al. (2016) focused on reducing taxi idle travel distance while maintaining service quality. Ma et al. (2017) designed an AV sharing and reservation model that optimally schedules AVs to serve the maximum number of customers. The AV taxi dispatch strategies in Hyland and Mahmassani (2018) were to minimize the total pickup distance when multiple requests enter the system. Zhang et al. (2017) formulated the ride-hailing vehicle assignment as a combinatorial optimization problem, which aims to maximize the global success rate of order acceptance. Korolko et al. (2018) formulated an integer program to match ride-hailing vehicles and passengers. The objective is to maximize total matching rewards that are arbitrarily defined. The fourth and emerging method is machine learning. Wen et al. (2017) proposed a reinforcement learning approach that adopts a deep Q-network to adaptively move idle vehicles to high-demand areas in a shared on-demand mobility system. Xu et al. (2018) also used reinforcement learning to solve a large-scale vehicle dispatch problem confronted by the ride-hailing company DiDi.

This chapter studies the potential of replacing current taxis with EAVs, especially the dispatch strategies of EAV taxis. We first design an EAV taxi simulation framework that can use different dispatch models. Then we propose an optimization dispatch model that aims at maximizing the total rewards of serving customers. By simulating the EAV taxi system dispatched by the optimization model, the data of optimal dispatch strategies are generated and used for training the neural network-based dispatch model. Finally, we evaluate and

compare the performance of the current taxis and EAV taxis in terms of customer service and operational efficiency.

4.2. Simulating EAV Taxi Operations

This section designs a simulation framework for the operations of EAV taxis. The simulation process is illustrated in Figure 4.1. A fleet of EAV taxis is initialized at the beginning of a day. The initial locations of the taxis could be drawn from real-world taxi operation data. The initial SOC is set randomly between 10% and 100%. Assume the taxi electric range is 200 miles and the electricity consumption rate is 0.3 kWh/mile (U.S. EPA, 2017). There are 5 status of an EAV taxi in the simulation—waiting, called, occupied, going to charging stations, and charging. The initial status is waiting, meaning that EAV taxis park somewhere and wait for picking up customers. At a time step T , we denote the set of available taxis as I and the set of customer requests as J . The available taxis could be the ones that are waiting or at the ending of charging (with $\geq 80\%$ SOC). The customer requests consist of the new ones that are just come in at the time step T as well as the unserved ones from the previous time steps. Assume the customers' maximum waiting time is 15 minutes; otherwise, the customers will stop requesting a taxi. The simulation uses a dispatch model to match a taxi $i \in I$ and a customer request $j \in J$. EAV taxis keep waiting or charging if not dispatched. If an EAV taxi gets dispatched, the status changes to called—the taxi goes to pick up the customer, and then occupied—the taxi is occupied by the customer. After dropping off the customer at the destination, the EAV taxi checks whether charging is needed. If battery SOC is higher than or equal to 10%, the taxi keeps waiting near the drop-off location for the next customer. If the battery SOC is less than 10%, the taxi goes to the nearest charging station and start charging. Once the SOC reaches 80%, the taxi becomes

available again for picking up new customers. If the taxi is not dispatched until the end of charging, it keep waiting near the charging station for incoming requests. The simulation uses 1 minute as the time interval, so the dispatch model is applied 1440 times per day. Taxi status and activities are updated and recorded simultaneously. A customer's waiting time increases by 1 minute if not accepted by any taxi at a time step.

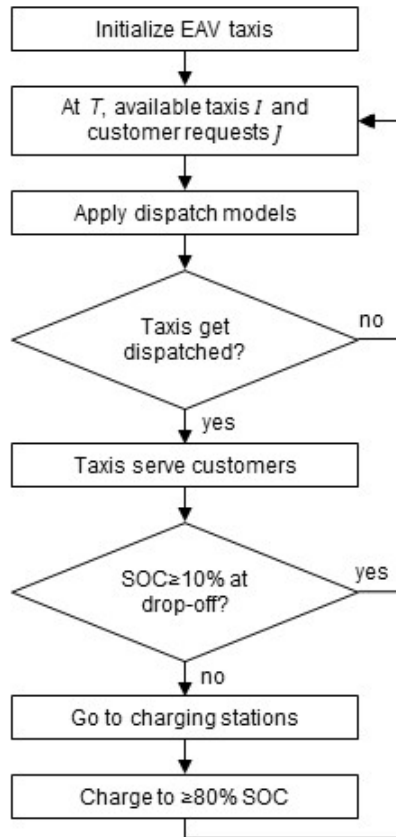


Figure 4.1 *The process of simulating EAV taxi operations.*

We use the NYC taxi trip data in the year of 2013 (Donovan and Work, 2016) to run the simulation. There are some additional explanations to the simulation. First, we use the locations of the expanded charging station networks of NYC showed in Section 3.3.1. We assume 50 kW fast chargers at all stations, as fast chargers are expected to be prevalent in the era of self-driving. Second, we use Equation 2-1 to estimate the travel distance of non-

occupied trips, because only occupied trip distance is recorded in the NYC taxi trip data. Third, taxis wait for new customer requests near the drop-off locations or charging stations. It is possible that taxis cannot park there for a long time and need to relocate, but we ignore the cruising distance for simplicity. Fourth, customers can only be served by EAV taxis, excluding other transportation services.

4.3. EAV Taxi Dispatch Models

4.3.1. Optimization Dispatch Model

At a time step T , there are I available taxis and J customer requests. The optimization-based dispatch model decides which EAV taxi $i \in I$ should pick up which customer request $j \in J$. The objective is to maximize total rewards collected from serving the J customers. The optimization model is constraint by customer waiting time, taxi-customer distance, and taxi battery range. To formulate the dispatch model, we first define the parameters as follows.

R_i : Remaining range of taxi i , $\forall i$ (mile);

T_{max} : Maximum pickup travel time (min);

D_j^t : Trip distance of customer request j , $\forall j$ (mile);

T_j^w : Waiting time of customer request j , $\forall j$, that is the time that the customer has waited for being accepted by a taxi (min);

$D_{i,j}^p$: Pickup travel distance for taxi i and customer request j , $\forall i, j$ (mile), calculated based on the GPS locations of taxi i and customer request j ;

$T_{i,j}^p$: Pickup travel time for taxi i and customer request j , $\forall i, j$ (min), calculated based on the pickup travel distance $D_{i,j}^p$ and travel speed;

$r_{i,j}$: Rewards if taxi i picks up customer request j .

The EAV taxi dispatch problem is formulated as an integer linear programming (ILP) model. The binary decision variables are $x_{i,j}$. $x_{i,j}$ equals 1 when taxi i is assigned to request j . The objective function is defined in Equation 4-1, which maximizes the total rewards collected from picking up customer requests J .

$$\max \sum_i \sum_j r_{i,j} x_{i,j} \quad (4-1)$$

subject to

$$\sum_j x_{i,j} \leq 1, \quad \forall i \quad (4-2)$$

$$\sum_i x_{i,j} \leq 1, \quad \forall j \quad (4-3)$$

$$(R_i - D_{i,j}^p - D_j^t) \cdot x_{i,j} \geq 0, \quad \forall i, j \quad (4-4)$$

$$(T_{max} - T_{i,j}^p) \cdot x_{i,j} \geq 0, \quad \forall i, j \quad (4-5)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall i, j \quad (4-6)$$

We define the reward $r_{i,j}$ of dispatching taxi i to customer j in Equation 4-7, where M is a sufficiently large number. The reward decreases as the pickup travel time $T_{i,j}^p$ becomes longer. The customer's waiting time T_j^w acts as the level of emergency that the he/she needs to be picked up. Our optimization model gives higher priority of dispatching taxis to the customers who have waited for longer time. For example, when two customer requests have the same travel time to a taxi, the model will decide to assign the taxi to the customer with longer waiting time due to the reward is higher. Many previous optimization models did not consider the waiting time of customers (Hyland and Mahmassani, 2018; Lu et al., 2018; Ma et al., 2017; Miao et al., 2016; Qu et al., 2014; Sheppard et al., 2017); thus taxi dispatching is not very fair to these customers, especially during rush hours.

$$r_{i,j} = M - T_{i,j}^p + T_j^w \quad (4-7)$$

The objective of optimal dispatch is subjected to the following constraints. Each taxi will serve at most one customer request, and each customer request will be served by at most one taxi, as shown by the constraint sets 4-2 and 4-3, respectively. Dispatching an EAV taxi is also subjected to the taxi's remaining range. If the remaining range of taxi i is not enough for picking up customer request j and dropping off the customer at the destination, taxi i will not be assigned to the customer. This constraint set is showed as 4-4. The constraint set 4-5 avoids that taxis travel long distance to pick up customers. The pickup travel time should be no more than the maximum pickup time T_{max} (assumed as 30 minutes). The constraint set 4-6 requires the decision variables to be binary.

4.3.2. Neural Network-Based Dispatch Model

The major drawback of the optimization-based dispatch model is that solving the ILP is computationally intensive, especially when a large amount of taxis and customer requests are involved. It is desired to develop both fast and accurate dispatch models. Neural networks could take long time to train, but when it calculates the outputs, the algorithms are simple. Therefore, the neural network-based models could be more efficient in dispatching EAV taxis than solving the ILP model of the same size. Also, neural networks can be more powerful in classification than other shallow models, such as logistic regression.

When a customer is requesting for a taxi, his/her current location, destination, trip distance, trip travel time, and waiting time are available to the central dispatch system. The dispatch system finds all the available taxis for this request. For each pair of the request and taxi ($i-j$), there are 11 input variables to the neural network dispatch model, as listed in Table 4.1. The 11 input variables include the taxis status (location and remaining range), the request status (location, trip distance, trip travel time, and waiting time), the spatial and

temporal relationship between taxi i and request j , and the current time. The neural network dispatch model calculates the probability of dispatching taxi i to request j .

Table 4.1 *Inputs of the neural network-based dispatch model.*

Input variable	Description
N_1	The GPS longitude of taxi i .
N_2	The GPS latitude of taxi i .
N_3	The remaining range of taxi i (mile).
N_4	The GPS longitude of customer request j .
N_5	The GPS latitude of customer request j .
N_6	The trip distance of customer request j (mile).
N_7	The trip travel time of customer request j (min).
N_8	The waiting time of customer request j (min).
N_9	The pickup travel distance from taxi i to customer request j (mile).
N_{10}	The pickup travel time from taxi i to customer request j (min).
N_{11}	Timestamp, the minutes elapsed relative to the beginning of the day.

The neural network consists of 1 input layer (11 neurons), 3 hidden layers (128, 64, and 8 neurons, respectively), and 1 output layer, as shown in Figure 4.2. The 3 hidden layers are activated by the ReLU function. We implement dropout with the drop rate of 0.2 following the first and second hidden layers to prevent overfitting. The output layer uses the sigmoid function to output the probability of dispatching taxi i to request j .

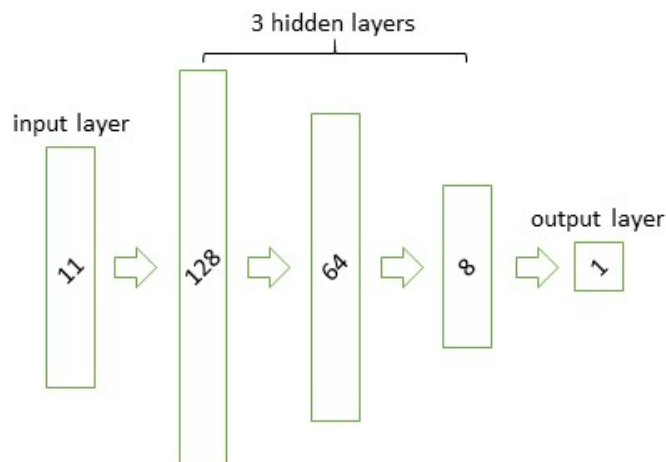


Figure 4.2 *Architecture of the neural network-based dispatch model.*

The output probability of the neural network alone is not enough to determine which taxi should be dispatched to which request. Since a taxi is possible to pick up any nearby requests, and a request could be served by any nearby taxis, there are overlaps among the taxi-request pairs. This problem can be illustrated in Figure 4.3. For example, the probabilities that taxi 3 is dispatched to request 1, 2, and 3 will all be calculated by the neural network, but taxi 3 can pick up only one request.

To solve the overlapping problem, we add an algorithm (see Algorithm 4.1) following the neural network outputs to make the final dispatch decisions. First, find the largest dispatching probability from the outputs. If the largest probability is smaller than 0.5, stop dispatching taxis. If the largest probability is larger than or equal to 0.5, find the corresponding pair of taxi i and request j . Dispatch the taxi i to pick up the request j . Then remove all the taxi-request pairs that have taxi i or request j . Iterate this process until all taxis in I have been dispatched or all customer requests in J can be served.

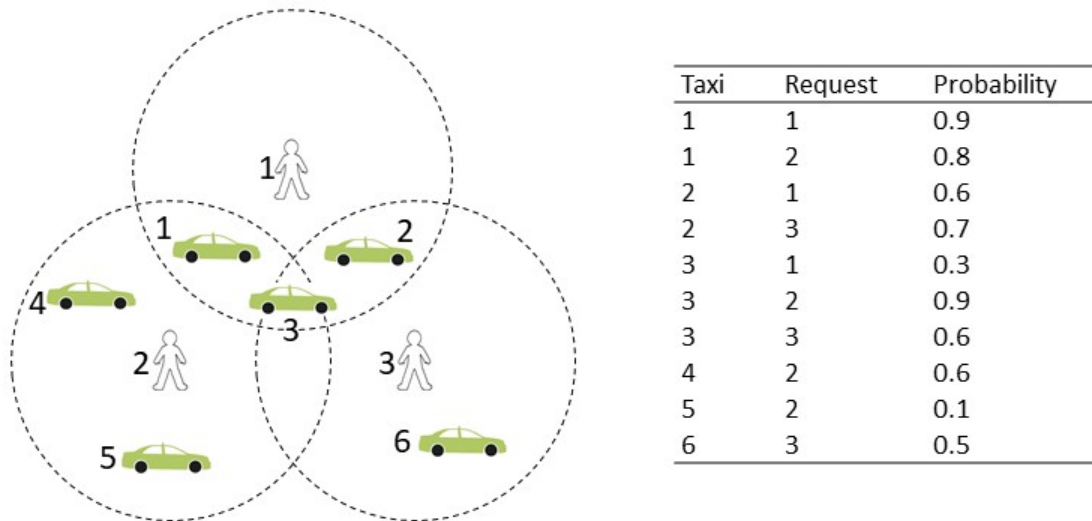


Figure 4.3 The overlaps among taxi-request pairs.

Algorithm 4.1 Make dispatch decisions following the neural network outputs

Input: available taxis I ,
customer request J ,
taxi-request pairs i - j ($i \in I, j \in J$),
probabilities of dispatching $p_{i,j}$ ($i \in I, j \in J$)

Output: which taxi i should be dispatched to pick up which customer request j

```

1:  while  $I \neq \emptyset$  and  $J \neq \emptyset$  do
2:      find the largest probability of dispatching  $p^{max}$ 
3:      if  $p^{max} \geq 0.5$  then
4:          Find the corresponding  $i$ - $j$  pair
5:          Dispatch the taxi  $i$  to the request  $j$ 
6:          Remove all the taxi-request pairs that have  $i$  or  $j$  and the dispatching probabilities
7:           $I \leftarrow I - i$ 
8:           $J \leftarrow J - j$ 
9:      else then
10:         break
11:     end if
12: end while

```

4.3.3. Training Neural Network-Based Dispatch Model

We let the neural network-based dispatch model learn the optimal dispatch decisions made by the optimization dispatch model. We select 3 consecutive days from September 10, 2013 00:00 to September 12, 2013 23:59 to simulate the EAV taxi operations using the optimization dispatch model. In order to achieve faster computation, we randomly draw 5% of taxis and 5% of served customer requests from the 3-day dataset to run the simulation. Previous works that simulated fleet operations often draw a proportion of all trip demand. For example, Chen et al. (2016) used 10% of all trip demand in a metropolitan area to simulate a fleet of shared EAVs, and Fagnant et al. (2015) simulated shared AVs that serve 5% of all vehicle trips on a 5% capacity network.

At each iteration of the simulation, the optimal dispatch decisions are made and the dispatch data (as listed in Table 4.1) of each taxi-request pair are generated. If taxi i is dispatched to request j , the dispatch decision is labeled as 1; otherwise, labeled as 0. The

optimal dispatch decisions generated during the 3-day simulation are used for training the neural network-based dispatch model.

Since the optimization-based dispatch model does not allow taxis to pick up the customers who are far away, we remove the dispatch data in which the taxi-to-customer travel time is beyond T_{max} and obtain about 10 million data samples. 90% of the data are used for training the neural network and 10% for validating. Only 1% of the training data are labeled as 1. We use up-sampling method to keep balance of the classes so the numbers of major and minor classes in the training data are equal.

We use the Adam optimizer and the binary cross entropy loss function to train the neural network for 100 epochs. The batch size is 256. The training and validation loss are shown in Figure 4.4. The validation losses do not show signs of overfitting. After training and validating for 100 epochs, the validation loss is 0.1888 and the validation accuracy is 0.9075. The recall on the validation dataset is 0.93, indicating that it is very unlikely to mistakenly predict a taxi-customer pair that should be matched as not matched. The neural network-based dispatch model is able to learn most of the optimal dispatch strategies.

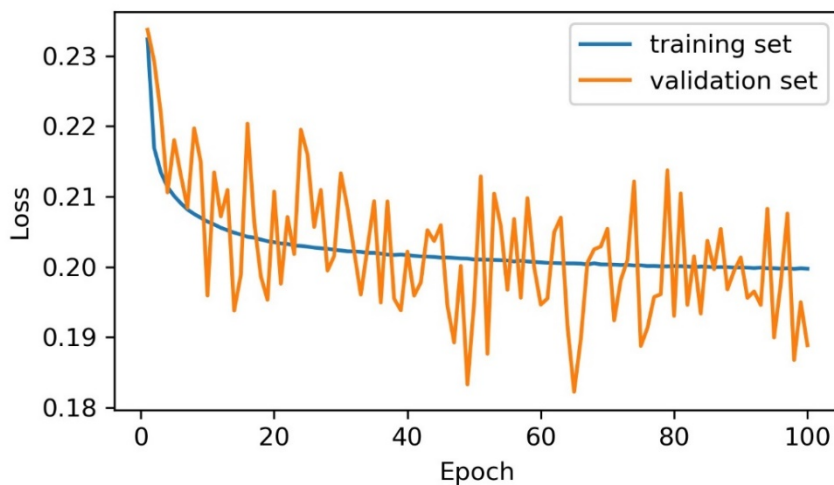


Figure 4.4 Training and validation losses.

4.4. Results

To make comparisons to the performance of the neural network-based dispatch model and the optimization-based dispatch model, we select another day October 16, 2013 for simulating EAV taxis dispatched by the 2 models, respectively. We draw 5% of taxis (650 taxis) and the customer requests they have served as the samples from this day's dataset. We again generate optimal dispatch data for this day and use them as an independent testing dataset. Implementing the neural network dispatch model to the testing dataset, the model accuracy is 0.8653 and the recall is 0.92. Logistic regression has testing accuracy of 0.8191 and recall of 0.87, which is less powerful to generate optimal dispatch solutions.

4.4.1. Performance of Dispatch Models

The optimization and the neural network dispatch models have similar performance in term of customer service, making EAV taxis serve 99.3% and 99.2% of the customer requests, respectively. Less than 1% fail to request taxis within the allowed waiting time. By contrast, using the logistic regression model makes 9.5% of customers fail to request taxis. Taxi pickup time is the travel time to the customer request once the taxi is dispatched. Under the optimization model, 76% and 92% of served customers can be picked up within 5 and 10 minutes, respectively, while it is 83% and 93% under the neural network model. In addition, over 90% of all customer requests can be immediately accepted by taxis under the 2 dispatch models.

In terms of the performance of the EAV taxi fleet (seen in Table 4.2), the average travel distance of the EAV taxis that are dispatched by the neural network model is 130.4 miles, which is 3% shorter than the optimally dispatched taxis. This is mainly due to the reduced empty travel distance. The average occupied trips and time spent for charging under

the two models are similar. The logistic regression model, by comparison, makes EAV taxis complete less occupied trips since 9.5% of customers cannot be picked up.

Based on the above comparisons, it is found that the neural network model has learnt the optimal dispatch solutions and its performance is very close to the optimization model.

Table 4.2 *Performance of EAV taxi fleet under different dispatch models.*

	Optimization-based model	Neural network-based model	Logistic regression-based model
Avg. occupied trips	36.2	36.1	33.0
Avg. travel distance (mile)	134.9	130.4	131.0
Avg. empty travel distance (mile)	34.1	29.8	39.6
Avg. distance occupancy	0.758	0.777	0.710
Avg. time spent for charging (min)	44.7	42.7	44.8

4.4.2. Computation Time of Dispatch Models

The simulation of EAV taxi operations using different dispatch models runs on a workstation with Intel Xeon E5-1620 CPU and 16GB RAM. The optimization-based dispatch models are solved by Gurobi 8.0.1. We record the time spent for obtaining dispatch solutions at each time step during the simulation. Figure 4.5 shows the histograms of the computational time. The optimization dispatch model takes 0~120 seconds to solve; the average computation time is 42.9 seconds. The neural network is much faster to obtain dispatch solutions. The average computation time is 9.9 seconds, and there are 95% chances it is within 15 seconds.

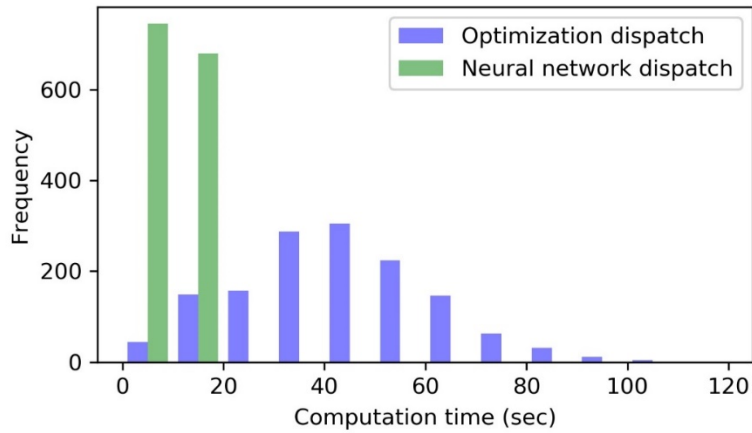


Figure 4.5 Histograms of computation time of different dispatch models.

We've also compared the average computation time with 95% confidence interval using different taxi sample sizes, as seen in Figure 4.6. When the models are dispatching EAV taxis of a larger fleet size, the average computation time of the optimization model increases much more significantly than the neural network model. In Figure 4.7, we use the 2 models to dispatch all taxis at different times of the day, respectively. It is found that the neural network dispatch model is still much more efficient to make dispatch decisions. Overall, since the neural network model has near-optimal dispatch solutions and is much faster to compute, it is more preferable for real-time EAV taxi dispatching.

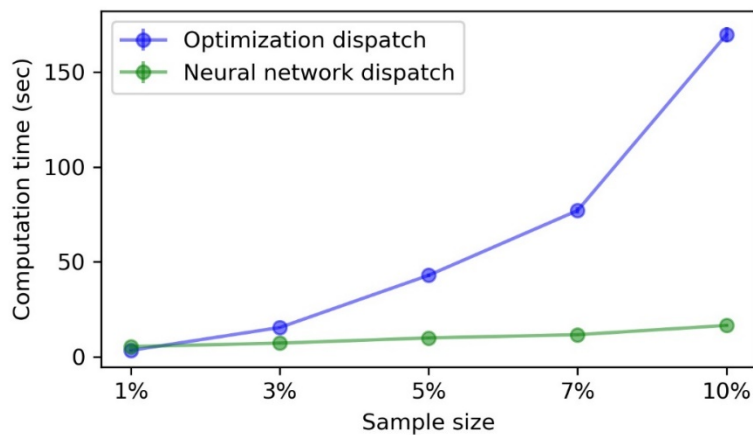


Figure 4.6 Average computation time using different taxi sample sizes.

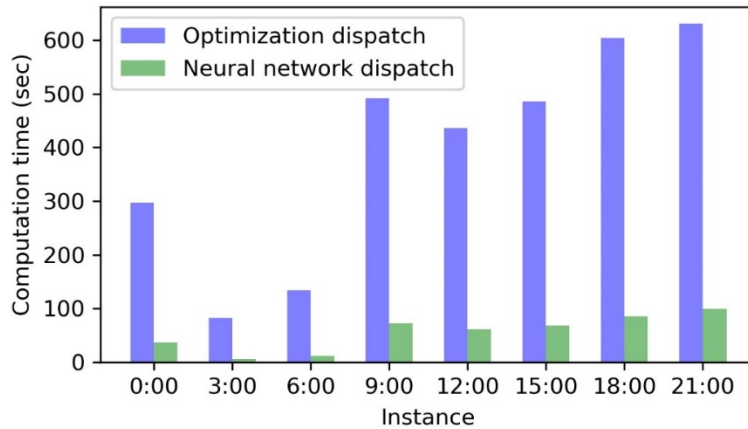


Figure 4.7 *Computation time of different instances using all taxis.*

4.4.3. Improvements to Taxi Operational Efficiency

The operational efficiency of current taxis can be improved by EAV taxis dispatched by the neural network-based model, in terms of total travel distance, empty travel distance, and travel distance occupancy, as shown in Figures 4.8, 4.9 and 4.10.

On the simulated day, the sampled current taxis travelled 157.8 miles on average to serve the customers. The travel distance distribution is more left-skewed. If the current taxis are replaced by EAV taxis that are dispatched by the neural network model, the average travel distance can reduce by 17% to 130.4 miles. EAV taxis' shorter travel distance is mainly due to the declined empty distance. The average empty travel distance decreases from 52.6 miles to 29.8 miles, a 43% reduction. EAV taxis also improve distance occupancy, the ratio of the travel distance occupied with customers over the total travel distance. The average distance occupancy increases from 67% to 78%, which indicates lower operation cost for the EAV taxis.

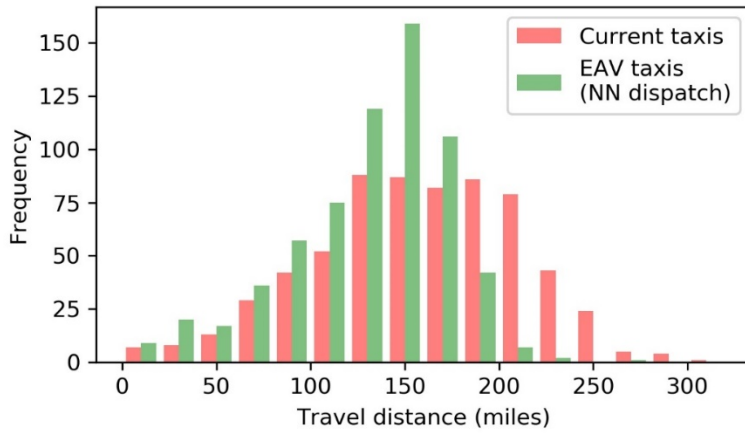


Figure 4.8 Histograms of total travel distance for current taxi and EAV taxi.

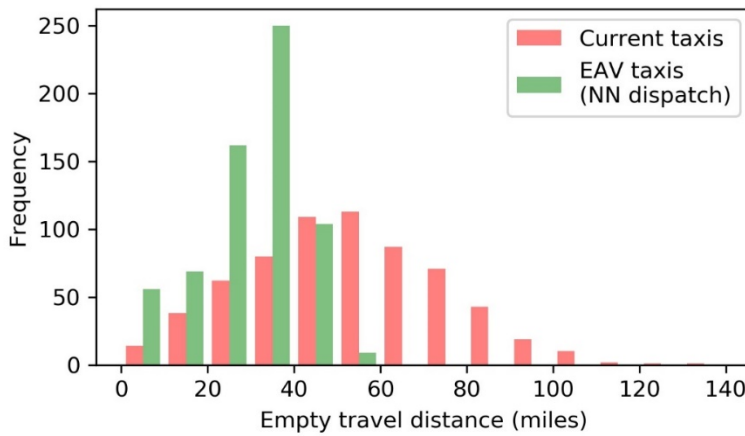


Figure 4.9 Histograms of empty travel distance for current taxi and EAV taxi.

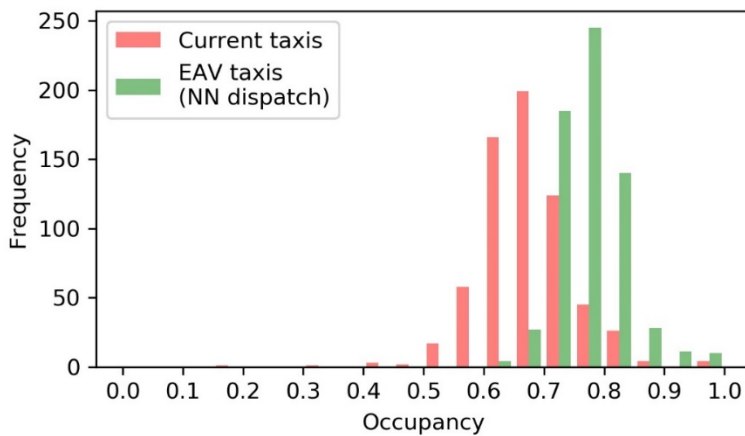


Figure 4.10 Histograms of travel distance occupancy for current taxi and EAV taxi.

4.4.4. Reduction in Fleet Size

EAV taxis have the potential to operate with fewer vehicles. We experiment with the fleet size of EAV taxis that are dispatched by the neural network model. The level of service and operational efficiency are shown in Table 4.3. EAV taxis become busier with smaller fleet size, in terms of more occupied trips, longer travel distance, and longer time spent for charging. The percentage of unserved requests increases from 0.7% to 2.1%. Over 80% of served customers can be picked up within 5 minutes, no matter what the fleet size is. The percentage of immediately accepted requests drops relatively faster, but the EAV taxis of 80% of fleet size can still let 75% of customer requests be accepted without waiting.

Table 4.3 *Level of service and operational efficiency of EAV taxis of different fleet sizes.*

	650 EAVs	618 EAVs	585 EAVs	553 EAVs	520 EAVs
Reduction in fleet size	0%	5%	10%	15%	20%
Unserved requests	0.8%	0.9%	1.0%	1.3%	2.1%
Taxi pickup time ≤ 5 min	83%	82%	82%	81%	82%
Requests accepted immediately	93%	90%	87%	83%	75%
Avg. occupied trips	36.1	38.0	40.1	42.3	44.6
Avg. travel distance (mile)	130.4	137.8	146.2	154.7	163.1
Avg. empty travel distance (mile)	29.8	32.1	34.9	37.5	39.9
Reduction in fleet travel distance	17.4%	17.0%	16.6%	16.6%	17.3%
Avg. time spent for charging (min)	42.7	44.7	48.8	53.1	54.1

When the fleet size reduces by 15%, an EAV taxi travels 154.7 miles daily on average, which is close to the current taxi. However, the average empty travel distance drops by 15.1 miles compared to the current taxi fleet, and 16.6% of fleet total travel distance can be saved. Therefore, EAV taxis can reduce fleet size by 15% while maintaining comparable

level of service and traveling less miles. In other words, 1 EAV taxi can replace about 1.2 current taxis.

4.5. Conclusions and Discussions

This chapter studies the dispatching problems of EAV taxis. We first design a simulation framework that can use different dispatch models for the operations of EAV taxis. Then we propose two EAV taxi dispatch models—the optimization-based model, which aims at maximizing total rewards collected from serving customers, and the neural network-based model, which learns the optimal dispatch strategies from the optimization model. Three consecutive days in 2013 are randomly selected for simulating the operations of EAV taxis that are dispatched by the optimization model in New York City. The data of optimal dispatch strategies are generated during the simulation process. The neural network dispatch model is trained using the generated data, in order to learn the optimal dispatch solutions.

We randomly choose another day for simulation to compare the performance of the two dispatch models. The results show that neural network dispatch model has learnt the optimal dispatch strategies and has very close performance with the optimization dispatch model in terms of customer service and taxi operational efficiency. In addition, the neural network model is much faster to make dispatch decisions, which is more preferable for real-time EAV taxi dispatching.

The EAV taxis dispatched by the neural network model can improve the operational efficiency of current taxis. On average, EAV taxis can reduce travel distance by 17%, reduce empty travel distance by 43%, and increase distance occupancy from 67% to 78%, while serving 99.2% of customer requests. By experimenting with the EAV taxi fleet size, it is found that EAV taxis can reduce fleet size by 15% while maintaining comparable level of service with the current taxi fleet and traveling shorter distance.

There are some limitations of this research. First, the simulation framework adopts deterministic charging rules. Future research can schedule EAV taxi charging ahead of time. For example, let taxi charge during low-demand hours to prepare for serving advanced peak demand. Second, idle EAV taxis do not relocate in the simulation. Relocating EAV taxis from low-demand areas to high-demand areas, however, can potentially save customers' waiting time. This research focuses on the dispatch problems of EAV taxis. More complex charging and relocation models will be studied in future research. Third, we sample only 5% of taxis and customer requests to run simulation due to limited computation power. In practice, the size of dispatching problems could be much bigger. We will draw more samples and generate more dispatch data for training the neural network model if more computation resources are available.

CHAPTER 5. MODELING CHARGING BEHAVIOR OF BATTERY ELECTRIC VEHICLE DRIVERS: A CUMULATIVE PROSPECT THEORY BASED APPROACH

5.1. Introduction

Promoting the use of battery electric vehicles is regarded as an effective way to reduce emissions and dependence on petroleum. Due to the limited battery range and insufficient charging infrastructure, BEV drivers need to pay attention to their battery state-of-charge and make proper charging plans to avoid driving with low SOC and experiencing the “range anxiety” phenomenon (Neubauer and Wood, 2014). Better understanding of BEV drivers’ charging behavior, such as determining the SOC when charging occurs, and choices of charging time and location (home, workplace, or public), will provide guidance to BEV use, charging infrastructure planning, and power grid capacity expansion.

The charging decisions of electric vehicle drivers have been modeled using simple and deterministic rules. For example, Kang and Recker (2009), Darabi and Ferdowsi (2011), and Kongthong and Dechanupapritta (2014) assumed that only home charging took place. Dong and Lin (2012) quantified the benefit and cost of a charge and assumed drivers decided to charge only if the benefit-to-cost ratio was larger than one. Hu et al. (2018) and Yang et al. (2016) assumed BEV taxi drivers would go to charging stations only if the SOC drops below a certain level. These papers help us understand the travel and charging patterns of EVs in the early adopter stage. However, these assumptions may not reflect realistic behaviors because charging behavior is not always deterministic and can be influenced by various factors. To overcome these limitations, random utility theory (RUT) was introduced to describe drivers’ decision-making about charging while operating under uncertain conditions and randomness. For example, Daina et al. (2017) developed a joint random utility model of

charging and activity-travel timing choices that takes various utilities across individuals into account. To incorporate heterogeneity among decision-makers, mixed logit choice models with random coefficients were developed to describe the decision to charge at the end of each trip (Zoepf et al., 2013), fast charging station choices (Sun et al., 2016), and charge timing choices (Langbroek et al., 2017).

One of the basic assumptions of RUT is that individuals are rational decision-makers who maximize utility relative to their choices. However, the assumption that decision-makers are rational has long been challenged (Kahneman and Tversky, 1979; Durbach and Stewart, 2012; Ilin and Rogova, 2017). In transportation research, irrational behaviors have been observed and modeled for departure time choice (Mahmassani and Chang 1986, Schwanen and Ettema 2009) and route choice (Zhou et al. 2014).

To take the limited rationality in decision-making into account, cumulative prospect theory was introduced. CPT is a behavioral science theory that describes the extent of decision-makers' attitudes and preference toward risk (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). The theory proposes that decision-makers (1) are risk-averse when outcomes are framed as gains relative to a reference point, and risk-seeking when outcomes are framed as losses; (2) are more sensitive to losses than gains; and (3) tend to apply too much weight to unlikely outcomes and too little weight to likely outcomes. CPT has been applied in many transportation research fields, such as route choice (Avineri and Bovy, 2008; de Luca and Di Pace, 2015; Gao et al., 2010; Wang and Xu, 2011; Xu et al., 2011; Yang and Jiang, 2014; Zhang et al., 2018; Zhou et al., 2014), commuter departure time choice (Senbil and Kitamura, 2004; Schwanen and Ettema, 2009), public-transport users' mode choice at transfer stations (Ceder et al., 2013), use of the high-occupancy-vehicle lane

(Chow et al., 2010), classification of the risk attitude of travelers (Yang et al., 2015), and congestion pricing (Liu et al., 2010). These studies all found success in using CPT to describe people's limited rationality and risk attitudes when making decisions. Among these works, Schwanen and Ettema (2009), Gao et al. (2010), Xu et al. (2011), Wang and Xu (2011), and Yang and Jiang (2014) compared CPT with utility theory expectations and showed that CPT is a better approach to modeling travelers' behavior.

When driving a BEV, there are no significant perceivable gains if the trip distance falls below the BEV range, but if the distance unexpectedly exceeds the range and the driver is caught on the road or forced to detour to reach a public charger, the losses are perceivably large. Moreover, BEV drivers tend to recharge at high battery SOC to avoid range anxiety. Therefore, the charging behavior of BEV drivers is in accordance with the rationale of CPT. This chapter proposes an innovative modeling framework for the charging behavior of BEV drivers based on CPT.

By applying the CPT-based charging behavior model, this chapter examines the collective effects of nationwide BEV charging under a mature market. A BEV mass-market scenario is constructed based on the 2017 National Household Travel Survey. By aggregating individuals' charging behavior, we can examine the distribution of battery SOC at the start of charging events, charging timing and location choices, and charging power demand profile. Sensitivity analyses are conducted to explore the influences of BEV drivers' attitudes toward risk on charging behavior and the influences of the public charger network coverage on the power grid.

5.2. Methodology

CPT describes an individual's decision-making process when confronted with uncertain outcomes and risks. The charging behavior modeling framework consists of two

phases—editing and evaluation—as shown in Figure 5.1. Based on the dwell and trip characteristics of a BEV, the editing phase confirms the outcomes of charging or not charging by the cost functions. The outcomes are converted to values (either gains or losses) relative to a reference point. Then the model considers the distribution of outcomes and estimates the corresponding probabilities. Weighting functions convert these probabilities into decision weights. In the evaluation phase, the prospects of charging or not charging are computed, and BEV drivers make charging decisions based on these prospects. The battery SOC and travel distance to the next charger are updated based on the charging decision. The following sections describe the modeling framework in detail. All the parameters of the modeling framework and their values are listed in the Appendix.

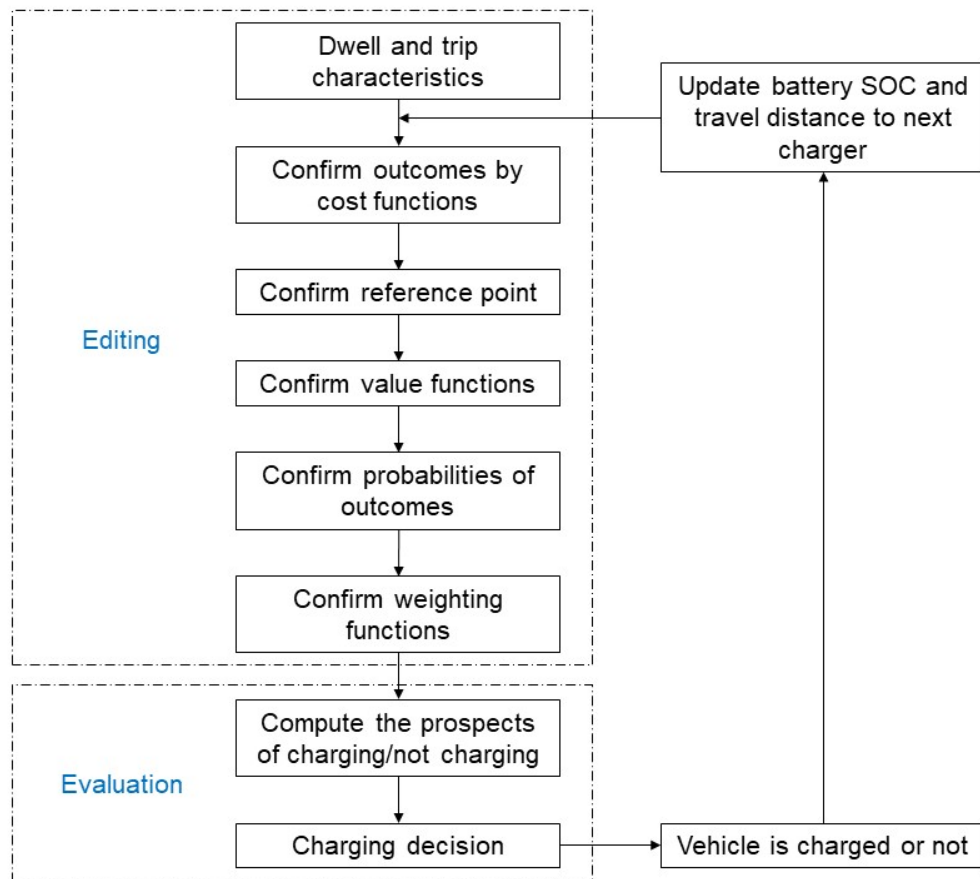


Figure 5.1 CPT-based charging behavior modeling framework.

5.2.1. Cost Functions

BEV drivers make a charging decision when a charger is available at the dwell location. The decision could be affected by the current SOC (the remaining range over full battery range, in %), charger power, charging cost, distance to the next charger, dwell time, dwell location, etc. The charging decision has a direct impact on the remaining range at the next charger (Equation 5-1).

$$r_n = r_c + r_i - d \quad (5-1)$$

where

r_n is the remaining range at the next charger (mile);

r_c is the current remaining range (mile);

r_i is the range increase (mile); and

d is the travel distance to the next charger (mile).

If the driver decides to charge the vehicle, the range increase is calculated as in Equation 5-2; otherwise, it is 0. Note that range increase should not surpass BEV full range.

$$r_i = \min\left(r_f - r_c, \frac{t_d \times P}{e_r}\right) \quad (5-2)$$

where

r_f is BEV's full range (mile);

t_d is dwell time (h);

P is charger power (kW); and

e_r is electricity consumption rate (kWh/mile), assumed 0.3 kWh/mile (U.S. EPA, 2017).

The remaining range at the next charger will result in different outcomes. Franke and Krems (2013) conducted a survey on 40 drivers of electric MINI Coopers which have a 104-mile range under normal driving conditions. They found that these drivers feel comfortable

when the battery SOC is above 20%~25%. However, when SOC drops below that comfort range, the drivers become anxious about using up electricity. This range anxiety phenomenon leads to unpleasant driving experiences. Therefore, this research considers 20 miles as the comfortable range threshold (r_a).

If a driver decides to charge the vehicle and arrive at the next charger with 20 miles or more range remaining, the costs for the driver consist of the charging hassle cost (c_h), charging service cost (c_s), and electricity cost (c_e). Kurani et al. (2009) and Axsen and Kurani (2009) found that BEV drivers perceived that recharging was not worth the hassle under certain circumstances. The value of time (VOT) is assumed as \$13.6/h for personal local travel and \$25.4/h for business local travel (U.S. DOT, 2016). Plugging and unplugging may take around 2 min (Dong and Lin, 2012; Wu et al., 2015; Wu et al., 2014), so we assume the charging hassle cost is \$0.45 if the trip is out of personal purpose and \$0.85 if the trip is out of business purpose. In addition, users typically pay a one-time service fee or a monthly membership fee to get access to public fast chargers. The charging service cost (c_s) is assumed as \$5 per charge (Francfort, 2015). The driver also needs to pay for the electricity, as calculated in Equation 5-3.

$$c_e = r_i \times e_r \times e_c \quad (5-3)$$

where

e_c is the electricity price, assumed as \$0.12/kWh (U.S. EIA, 2017).

If the driver has not arrived at the next charger but the remaining range drops below the comfortable point, r_a , there is a psychological cost for the driver as he/she becomes increasingly anxious as the remaining range decreases. Thus, we assume the psychological

cost increases linearly to the penalty cost (c_p) as the remaining range drops to 0. c_p equals \$109, which is the U.S. national average car towing cost (Moor, 2016).

Even though the driver has charged the vehicle, it is still possible that the vehicle will run out of electricity during the trip. When this happens, the driver has to pay for towing and travel to the destination by other means, such as taking a taxi.

Therefore, the outcomes of charging can be represented by the cost function $C_1(r_n)$ as below.

$$C_1(r_n) = \begin{cases} -c_h - c_s - c_e, & r_n \geq r_a \\ -c_h - c_s - c_e - \frac{r_a - r_n}{r_a} \times c_p, & 0 \leq r_n < r_a \\ -c_h - c_s - c_e - c_p - c_t \times |r_n|, & r_n < 0 \end{cases} \quad (5-4)$$

where

c_t is the taxi rate (\$/mile), assumed \$2.51/mile based on the data published on TaxiFareFinder (2018).

In contrast, the outcomes of not charging are represented by the cost function $C_2(r_n)$ as shown in Equation 5-5. There is no charging cost, but the driver runs a higher risk of feeling range anxiety or becoming stranded.

$$C_2(r_n) = \begin{cases} 0, & r_n \geq r_a \\ -\frac{r_a - r_n}{r_a} \times c_p, & 0 \leq r_n < r_a \\ -c_p - c_t \times |r_n|, & r_n < 0 \end{cases} \quad (5-5)$$

5.2.2. Reference Point and Value Function

The outcomes at the next charging opportunity are determined by the cost functions $C_1(r_n)$ and $C_2(r_n)$. The outcomes are framed as gains or losses when compared to a reference point (c_0). The reference point is defined as the cost of driving to the next charger, as shown

in Equation 5-6. The value function, shown in Equation 5-7 and Figure 5.2, considers gains and losses separately, and converts the outcomes to values for the decision-maker.

$$c_0 = -d \times e_r \times e_c \quad (5-6)$$

$$V(c) = \begin{cases} (c - c_0)^\alpha, & c \geq c_0 \\ -\lambda(c_0 - c)^\beta, & c < c_0 \end{cases} \quad (5-7)$$

where

α and β are the risk preference parameters ($0 < \alpha, \beta < 1$);

and λ is the loss aversion parameter ($\lambda > 1$).

The value function exhibits risk-aversion over gains and risk-seeking over losses. Larger values of α and β indicate that people are more sensitive to risk. λ is larger than 1, which suggests that people are more sensitive to losses than gains. Larger values of λ represent the increasing degree of sensitivity.

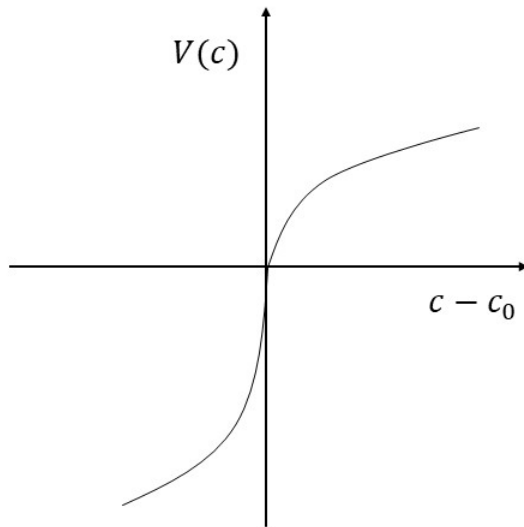


Figure 5.2 *Value function.*

5.2.3. Estimating Probabilities of Outcomes

The outcomes encountered by BEV drivers are uncertain, because the remaining range at the next charger, denoted by r_n^k , is not deterministic. The real world BEV electricity

consumption can be affected by ambient temperature (Wang et al., 2017), driving speed (Wager et al., 2016; Yi and Shirk, 2018), road gradient (Liu et al., 2017b), and use of air-conditioning (Liu et al., 2017a). Assume r_n^k follows the normal distribution

$$r_n^k \sim N(r_n, (cv \times r_n)^2) \quad (5-8)$$

where

cv is the coefficient of variation.

We use r_n estimated by Equation 5-1 as the mean for the normal distribution, and $cv \times r_n$ as the standard deviation. cv is 0.234 based on a FleetCarma dataset which includes travel activities of 436 2013/2014 Nissan Leafs in three U.S. states (California, Texas, and Maine) for about 7 months. The distance and electricity consumption of each trip are available. The average electricity consumption rate in a day is calculated as the ratio of the total daily electricity consumption to the total daily travel distance. The range is calculated as the battery capacity divided by the average electricity consumption rate. It was found that the mean and standard deviations of the LEAF's range are 96 miles and 22.5 miles, respectively, so the coefficient of variation is 0.234.

Note that r_n^k follows a continuous distribution. To apply CPT, we convert the normal distribution into a discrete distribution that generates 10 possible outcomes of the remaining range at the next charger with the associated probabilities. First, we construct a confidence interval (θ) with a level of confidence of $p\%$.

$$a = r_n - cv \times r_n \times \phi^{-1}(0.5 + 0.5 \times p\%) \quad (5-9)$$

$$b = r_n + cv \times r_n \times \phi^{-1}(0.5 + 0.5 \times p\%) \quad (5-10)$$

$$\theta = [a, b] \quad (5-11)$$

where

$\phi(\cdot)$ is the cumulative distribution function of standard normal distribution.

Convert the normal distribution to a truncated normal distribution that lies within the confidence interval θ . Divide θ into 10 equal intervals, denoted by $\Delta_1, \Delta_2, \dots, \Delta_{10}$. r_n^k serves as the median of interval Δ_k ($k = 1, 2, \dots, 10$), and the corresponding probability p_k is the probability that the remaining range falls in Δ_k . Note that p_k is also the probability of the outcome c_k associated with r_n^k .

5.2.4. Weighting Functions

CPT states that an event with a small possibility of occurring will generally be overestimated by decision-makers, whereas an event with a larger possibility of occurring will be underestimated, as illustrated in Figure 5.3. The cumulative decision weights $\pi(p)$ are defined in Equations 5-12 and 5-13 (Tversky and Kahneman, 1992). They are calculated based on the weighting functions $w(p)$, as seen in Equations 5-14 and 5-15, where the probabilities of gains and losses take different parameters, γ and δ . The parameters γ and δ indicate the extent of influence from overweighting and underweighting, and $0 < \gamma, \delta < 1$. The smaller γ and δ result in a more curved weighting function.

$$\pi_i^+(p_i) = w^+(p_i + \dots + p_n) - w^+(p_{i+1} + \dots + p_n) \text{ for } 0 \leq i < n \text{ and } \pi_n^+(p_n) = w^+(p_n) \quad (5-12)$$

$$\pi_j^-(p_j) = w^-(p_{-m} + \dots + p_j) - w^-(p_{-m} + \dots + p_{j-1}) \text{ for } -m \leq j < 0 \text{ and } \pi_{-m}^-(p_{-m}) = w^-(p_{-m}) \quad (5-13)$$

$$w^+(p_i) = \frac{p_i^\gamma}{[p_i^\gamma + (1-p_i)^\gamma]^{1/\gamma}} \quad (5-14)$$

$$w^-(p_j) = \frac{p_j^\delta}{[p_j^\delta + (1-p_j)^\delta]^{1/\delta}} \quad (5-15)$$

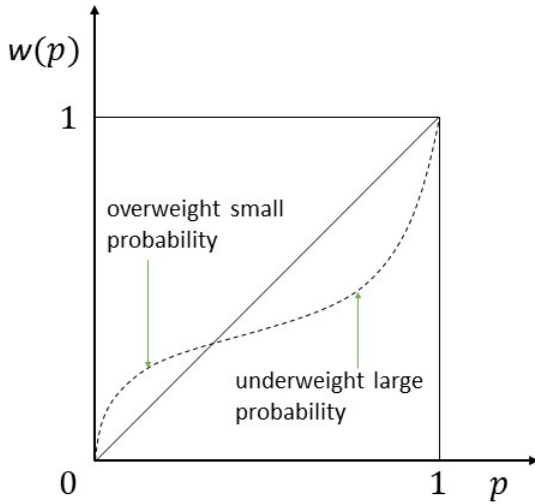


Figure 5.3 *Weighting functions.*

5.2.5. Charging Decision

BEV drivers make charging decisions based on cumulative prospect values. The cumulative prospect values of charging and not charging are calculated based on Equation 5-16.

$$U(c, p) = \sum_{i=0}^n \pi_i^+(p_i) V(c_i) + \sum_{j=-m}^{-1} \pi_j^-(p_j) V(c_j) \quad (5-16)$$

The probability of making the decision of charging (p_c) is calculated as follows:

$$p_c = \frac{e^{U_1}}{e^{U_1} + e^{U_2}} \quad (5-17)$$

where

U_1 is cumulative prospect value of charging the vehicle; and

U_2 is cumulative prospect value of not charging the vehicle.

Note that the charging probability p_c is calculated based on the next charging opportunity. When making charging decisions BEV drivers may think beyond the next charging opportunity and consider the itinerary of the travel day to plan for charging.

Therefore, the threshold probability of charging (p_t) is determined based on the remaining

travel distance and the number of charging opportunities before arriving at the last destination at the end of the day, as shown in Equation 5-18. If p_c is greater than p_t , the driver decides to charge; otherwise, the driver will not charge.

$$p_t = \frac{1}{1 + e^{-\frac{\varepsilon h}{l}}} \quad (5-18)$$

where

h is the number of later charging opportunities before arriving at the last destination of the day;

l is the travel distance from the current stop to the last destination of the day (mile); and

ε is the scale parameter.

Since the last destination of the day is usually home, $\frac{h}{l}$ indicates the charging opportunities per mile before returning home. When the charger coverage in the remaining itinerary is high, the threshold probability p_t is large and drivers are less likely to charge vehicles at the current stop. The scale parameter ε is used to adjust the impact of itinerary on the threshold probability, which is often seen in CPT applications (Jou and Chen, 2013; Lou and Cheng, 2016; Schwanen and Ettema, 2009; Zhang et al., 2018).

The CPT parameters indicate different risk attitudes among individuals. The driver's socioeconomic characteristics (e.g., income, gender, age, and education), BEV experience, charger familiarity, etc., have effects on the parameters. Calibration of these parameters is beyond the scope of this research. This research adopts the values calibrated by Tversky and Kahneman (1992): $\alpha = 0.88$, $\beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$ in the following analysis. In addition, sensitivity analyses are conducted to examine the impact of the parameters on charging behavior.

5.3. BEV Mass-market Scenario based on 2017 National Household Travel Survey

This study builds a BEV mass-market scenario based on the 2017 National Household Travel Survey. The scenario shows how to examine charging behavior in the long term under a mature BEV market with factors such as high BEV penetration, long range, and adequate charging infrastructure with more fast chargers available.

5.3.1. BEVs in 2017 NHTS

The 2017 NHTS is an inventory of the U.S. residents' travel behavior during a travel day, including trips made by all modes of transportation (U.S. DOT, FHWA, 2017). The VEHICLE file of the NHTS consists of 242,160 passenger vehicles (i.e., cars, SUVs, vans, or pickup trucks) owned by the respondents. The 2017 NHTS introduced a new field—HFUEL in the VEHICLE file—to indicate the type of powertrain. For example, HFUEL = 3 means that the vehicle is a BEV. There are 607 BEVs in the raw data. However, some respondents mistakenly reported their plug-in hybrid electric vehicles (PHEV), such as the Chevrolet Volt, Ford Fusion Hybrid, and Toyota Camry Hybrid, as BEVs. After removing these PHEVs, there are 392 BEVs remaining, as listed in Table 5.1. The BEV market penetration is a mere 0.16%. This survey showed that the Nissan Leaf (182 in total) and Tesla are the most popular models among BEV drivers in the U.S. The ranges of most BEV models are less than 100 miles.

The average travel distance during the travel day of non-Tesla BEVs (μ_{BEV}) is 28.1 miles, while the average travel distance of gasoline vehicles (μ_{GV}) is 34.7 miles. We compare the two means using the t-test. The alternative hypothesis is that the non-Tesla BEVs have a shorter average travel distance than gasoline vehicles; that is $H_a: \mu_{BEV} < \mu_{GV}$. The t-test shows that the p-value is 0, indicating the BEVs' average daily travel distance is significantly shorter than that of gasoline vehicles. The average travel distance of Teslas (μ_{Tesla}) is 41.2

mile. A t-test is conducted with the alternative hypothesis of $H_a: \mu_{Tesla} > \mu_{GV}$. The test shows that the Teslas' average daily travel distance is not significantly longer than gasoline vehicles (p-value is 0.0802). Since the BEV samples in the 2017 NHTS are inappropriate for studying charging behavior in a mature market, we constructed a BEV mass-market scenario using the 2017 NHTS with the assumption that some gasoline vehicles will be replaced by BEVs without changing their current travel patterns.

Table 5.1 *BEVs in 2017 NHTS.*

BEV make and model	Number of vehicles	EPA rated range (in miles)
Tesla	121	249*
2013/14/15 Nissan LEAF	117	84
2011/12 Nissan LEAF	45	73
Fiat 500e	27	87
2016/17 Nissan LEAF	20	107
Chevrolet Spark EV	17	82
Volkswagen e-Golf	14	83
Smart Fortwo electric drive	11	68
Ford Focus Electric	6	76
Toyota RAV4 EV	5	103
Kia Soul EV	5	93
Honda Fit EV	3	82
BMW ActiveE	1	94

*The model of Tesla is not available. Use 249 miles in this chapter.

5.3.2. Vehicle Travel Activities

The TRIP file of the 2017 NHTS recorded the trips of each person in the household during a travel day. The following filtering criteria were applied to select the personally operated vehicle (POV) trips on the travel day.

- TRPTRANS = 3, 4, 5, or 6 (the POV is a car, SUV, van, or a pickup truck);
- DRVR_FLG = 1 (identical POV trips are counted once).

The trip characteristics are listed in Table 5.2. The dwell time at a destination is derived from the time intervals between two continuous trips. After removing vehicles with

incorrect or missing fields, there are 153,776 vehicles left. Based on the trip and dwell characteristics, we can determine the vehicle travel activities during the day, as illustrated in Figure 5.4.

Table 5.2 Selected trip characteristic fields from the TRIP file.

Field	Description
HOUSEID	Household identifier.
VEHID	Vehicle identifier.
STRTTIME	Trip start time.
ENDTIME	Trip end time.
WHYFROM	Trip origin. Convert the values of 1 or 2 to 'home', 3 or 4 to 'work', and ≥ 5 to 'public'.
WHYTRP1S	Trip destination. Convert the values of 1 to 'home', 10 to 'work', and ≥ 20 as 'public'.
VMT_MILE	Trip distance for POV trips (mile).
DWELTIME	Time spent at the destination.

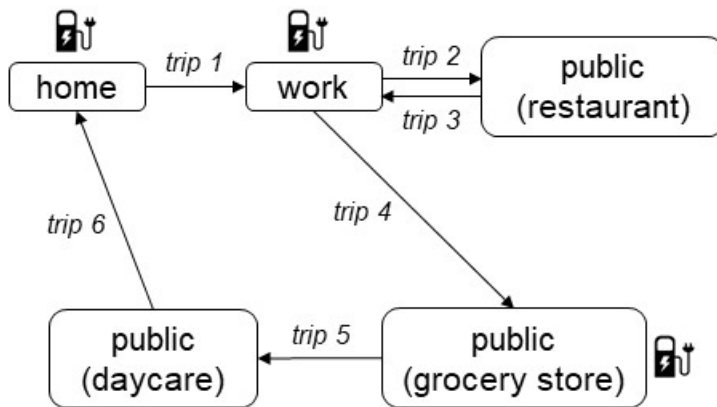


Figure 5.4 Travel activities of a sample vehicle during the day.

5.3.3. Charger Network Coverage and Charger Power

Wide BEV adoption is constrained by insufficient charger network coverage and low-speed chargers. Charger network coverage can be represented by the probability that a charger is available at the destination (Dong and Lin, 2012; Kontou et al., 2019). If a charger is available, BEV drivers may take advantage of the dwell time at the destination to charge

their vehicles without interfering with their travel plans (Dong et al., 2014; Hu et al., 2018). In this study, charger availability (X) is drawn from a Bernoulli distribution with probability p_a . $X = 1$ that means a charger is available; otherwise, $X = 0$.

$$\Pr(X = 1) = 1 - \Pr(X = 0) = p_a, \quad 0 \leq p_a \leq 1 \quad (5-19)$$

Homes, workplaces, and public locations offer different probabilities of having available chargers. For example, in Figure 5.4, this vehicle has charging opportunities at home, the workplace, and the grocery store. At each charger site, we calculate the travel distance to the next charging opportunity and apply the CPT model to determine the driver's charging decision.

Charger power also varies at different charging locations. Regular residential chargers are Level 2 of 3.3 kW and some are Level 2 of 6.6 kW (Francfort, 2015). The power of Level 2 chargers could increase to 19.2 kW (SAE, 2016). Direct current (DC) fast chargers of 50 kW have been introduced to the market and are gaining popularity (Saxton, 2013). The EV Project showed that current BEV drivers use AC Level 2 chargers (3.3 kW and 6.6 kW) most frequently (83% of all charging events), while 11% of charges are being performed using DC fast chargers (Smart and Scofield, 2014). This study considers Level 2 chargers with higher power and DC fast chargers in the mass-market scenario.

5.3.4. The BEV Mass-market Scenario

The Market Acceptance of Advanced Automotive Technologies (MA3T) model developed by Oak Ridge National Laboratory is a simulation tool for the U.S. vehicle market (Lin, 2014; Lin and Greene, 2011; Xie and Lin, 2017). MA3T uses a nested multinomial logit model to predict customer acceptance of advanced vehicle technologies, including BEVs. Under the “Developed” scenario that supposes a further expansion of charging

infrastructure with higher power, the model predicts that by 2030 the BEV market share is 17%, among which 58.7% are BEVs with a 100-mi range (BEV-100), 41.1% are BEV-200, and 0.3% are BEV-300 (Xie et al., 2018).

Accordingly, we selected $242,160 \times 17\% = 43,540$ vehicles from the 2017 NHTS as the BEV samples to build the mass-market scenario. The average weight is 869 (U.S. DOT, FHWA, 2017), indicating that a vehicle sample in the NHTS can represent 869 vehicles nationwide. Thus, the selected 43,540 vehicles can represent 37,836,260 BEVs in the country. The BEV range is assumed to be 100, 200, or 300 miles, and the shares are in accordance with the MA3T model predictions. Moreover, in the mass-market scenario there is an adequate charging infrastructure with more fast chargers available. It is assumed that BEV drivers all install chargers at home and out-of-home charging coverage is 0.5 at workplaces and in public locations (Tehrani et al., 2013). The scenario parameters are listed in Table 5.3.

Table 5.3 *Parameters of BEV mass-market scenario.*

Parameter	Value
BEV range (mile)	100, 200, or 300
Home charger network coverage	1.0
Work charger network coverage	0.5
Public charger network coverage	0.5
Home charger power (kW)	6.6
Work charger power (kW)	19.2
Public charger power (kW)	50
BEV market share	17%

The EV Project showed that the SOC is nearly always above 78% at the end of overnight home charging for Nissan Leaf drivers (Smart and Schey, 2012). Nissan also offers the option of stopping the charging once the SOC reaches 80% to preserve battery life when

full range charging is not necessary (Nissan, 2011). Since over 90% of vehicles in the 2017 NHTS started their travel day at home, this research assumes the battery SOC at the beginning of the first trip during the day is uniformly distributed between 78% and 100%.

5.3.5. Simulation

This study simulates the BEV mass-market scenario using the TRIP data in the 2017 NHTS and the CPT charging behavior model. For each sampled BEV, we first determined its travel activities during the day using the data fields listed in Table 2, including trip origin and destination, trip start time and end time, trip distance, and dwell time at the destination. As illustrated in Figure 4, a BEV travels 6 times that day and has 3 charging opportunities at work, in public (grocery store), and at home. When the driver arrives at the workplace, the BEV's remaining range r_c is updated, and the dwell time at the workplace t_d can potentially be used for charging with an increase of r_i miles. The travel distance to the next public charging opportunity (grocery store) d is the total distance of trips 2, 3, and 4. With these travel data as inputs, we apply the CPT charging behavior model to determine the driver's charging decision. If the driver decides to charge, the BEV's remaining range is updated when the charging session ends. By aggregating the individual's charging decisions, the collective effects of nationwide BEV charging under the mass-market scenario can be examined. When running the simulation, we have adjusted the dollar values of different years in the CPT model to the values of 2017 based on the inflation rates published by the U.S. Department of Labor (2019).

5.4. Results

5.4.1. Charging Behavior under the Mass-market Scenario

5.4.1.1. Battery SOC at the start of charging events

The battery SOC at which BEV drivers decide to charge is an important aspect of charging behavior. On one hand, drivers may want to charge at a higher SOC to avoid range anxiety; on the other hand, drivers may think charging is not worth the hassle. Therefore, BEV drivers charge their vehicles at a wide range of starting SOC levels. The EV Project showed that the majority of charging events started with a 20~80% SOC and the most frequent starting SOC levels are within 50~60% (Smart and Schey, 2012). Zou et al. (2016) found that about three-quarters of the BEV taxi drivers in Beijing, China did not resort to charging until the SOC dropped below 50% and most charging events started with a 40~50% SOC.

Figure 5.5 examines the distribution of battery SOC at the beginning of charging events under the mass-market scenario. On average, BEV drivers start charging at a 41% SOC. Most charge events start with a SOC between 40% and 50%. Seventy-three percent of all charge events occur when the SOC drops below 50%. BEV drivers do not often decide to charge at either very high or very low levels of SOC. Only 2.5% of charging events start with an 80% SOC or even higher, and only 7.5% of charging falls below the anxiety range of 20 miles. Compared with the EV Project observations in which most charges occurred at 50~60% SOC, drivers tend to charge at a lower SOC in the mass-market scenario. BEV drivers will be more confident with using the more of the battery range when the charging infrastructure is well established.

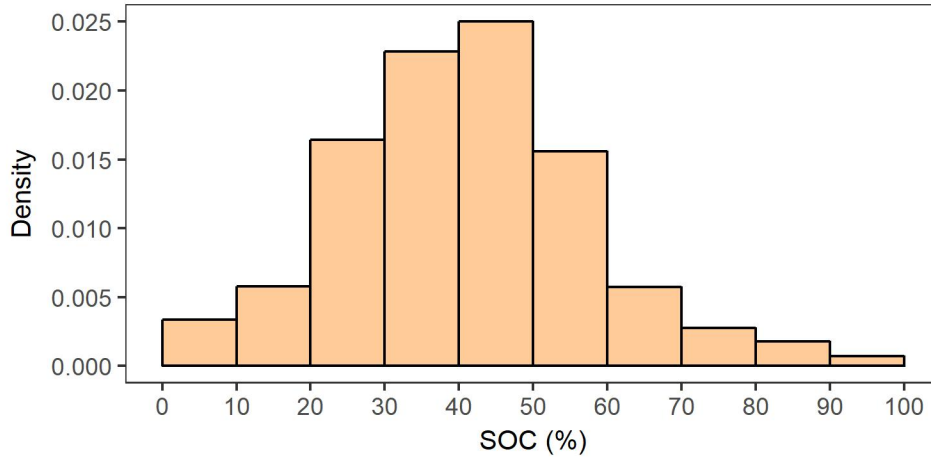


Figure 5.5 *Distribution of battery SOC at the start of charging events.*

The battery SOC before charging varied by charger location. The average starting SOC levels at home, workplace, and public chargers are 40.6%, 47.8%, and 39.1%, respectively. The average SOC at workplace chargers is higher, mainly because the drivers have not traveled a long distance when they first arrive at the workplace in the morning. The initial SOC is slightly lower for home and public charging. This is due to the higher cost associated with using public chargers.

5.4.1.2. Charge timing and location choices

BEV drivers may charge vehicles at different times of the day in different places. Figure 5.6 shows that the amount of vehicles undergoing charging and the proportions of charging location usage fluctuate during the day. In the morning, fewer BEVs choose to recharge, because either the vehicles have not consumed enough electricity to need a charge or the vehicles are in use. In the afternoon, the number of vehicles being charged starts to rise. The increasing rate is especially dramatic from 3 to 6 p.m. when people typically return home from work or other places. The number of charging vehicles peaks at 6 to 7 p.m.

The charging location also changes considerably during the day. From 6 to 9 a.m., over 60% of the charging vehicles are using workplace chargers. In the afternoon, the use of

public and home chargers rises and the workplace chargers are used less. The public chargers are mainly used in the daytime. The proportion of publicly charging vehicles is highest around noon, when drivers take advantage of lunchtime to recharge. Home chargers play the dominant role in BEV charging. Although the proportion of home charging drops dramatically in the morning, drivers prefer home charging during other times of the day, even if work and public chargers provide higher power. At night, almost all charging vehicles use home chargers.

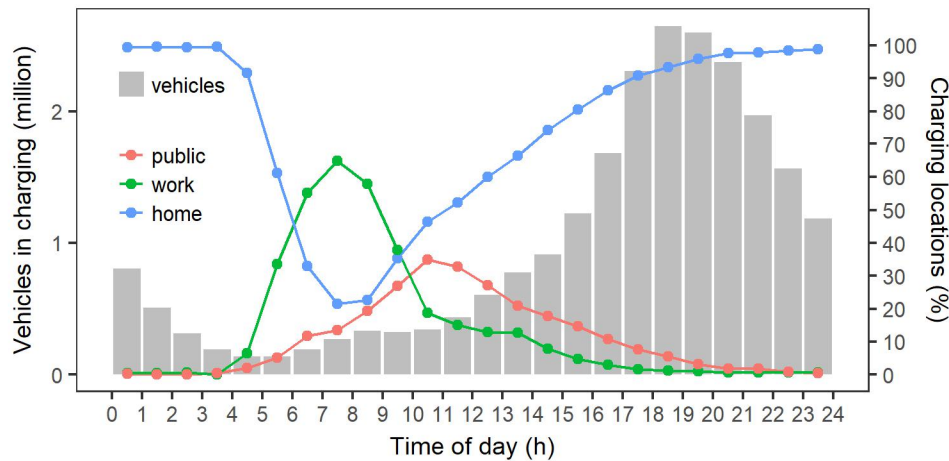


Figure 5.6 Number of vehicles in charging and the proportions by charging locations.

5.4.1.3. Charging power demand

Some of the concerns with mass adoption of BEVs relate to whether the current electrical grid capacity can accommodate the additional load (Green et al., 2011; Hardman et al., 2018; Liu, 2012; Moon et al., 2018). Figure 5.7 shows the charging power demand during the daytime and where the demand comes from. The load profile generally follows a trend similar to the number of charging vehicles during the day. In the morning, the power demand is the lowest and mainly comes from workplace chargers. Demand is at a moderate level from noon to 4 p.m. Note that during this time period, the power demand mainly comes from public chargers. Although home charging is more frequent than public charging, a

considerable share of the power demand during the daytime comes from public chargers. After working hours, since the majority of charging vehicles use home chargers, the load from home charging again accounts for the largest share. The load peak occurs between 5 and 8 p.m.

In summary, the three important characteristics of the BEV demands on charging power are (1) daytime load is higher than nighttime load; (2) daytime load mainly comes from workplace and public chargers, while nighttime load mainly comes from home chargers; and (3) the load contribution from workplace chargers peaks in the early morning, while the load contributed by public chargers peaks at noon.

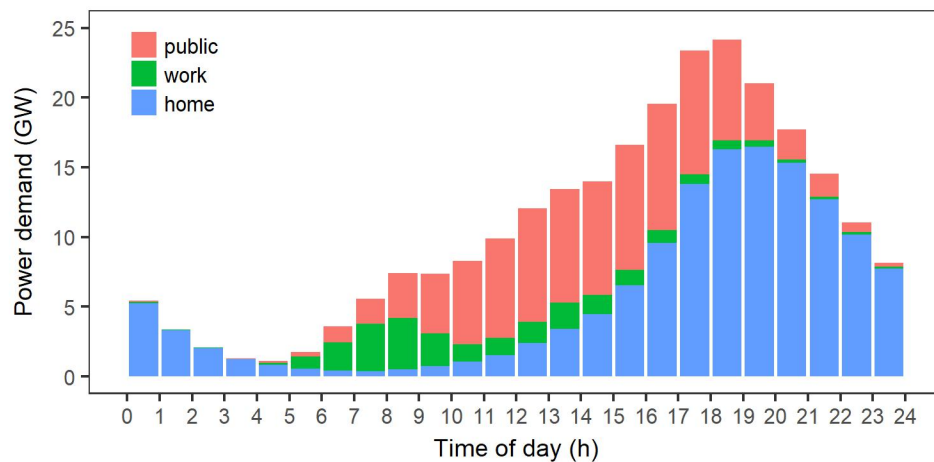


Figure 5.7 Charging power demand and the proportions by charging location.

5.4.2. Impacts of Driver Risk Attitude on Charging Behavior

The CPT model describes how people's attitudes toward risk affect the decision-making process. The parameters α and β in the value function (i.e., Equation 5-7) represent the risk preference of decision makers. Higher values of α and β indicate that decision makers have a greater degree of risk aversion; while lower values indicate a greater degree of risk seeking. λ is the loss aversion parameter. Lower values of λ represent the decreasing degree of sensitivity to losses over gains.

Figure 5.8 shows the impacts of risk preference parameters α and β on battery SOC at the start of charging and on the proportions of charges that begin with a 20-mile range (or less) remaining. Let $\alpha = \beta$, indicating the same risk preference for gains and losses (Schwanen and Ettema, 2009). By changing the values from 0.05 to 0.95, Figure 5.8 shows that drivers' risk preferences have a significant impact on charging behavior. As α and β increase, drivers become more risk averse, and the average starting SOC increases steadily. Meanwhile, the proportion of the charges with less than 20 miles SOC remaining decreases. The drivers who are more risk averse tend to charge vehicles at a higher SOC in order to avoid range anxiety. In contrast, when drivers are extreme risk seekers, the starting SOC (on average) is 33.4% and over 20% of all charges start with 20 miles or less remaining.

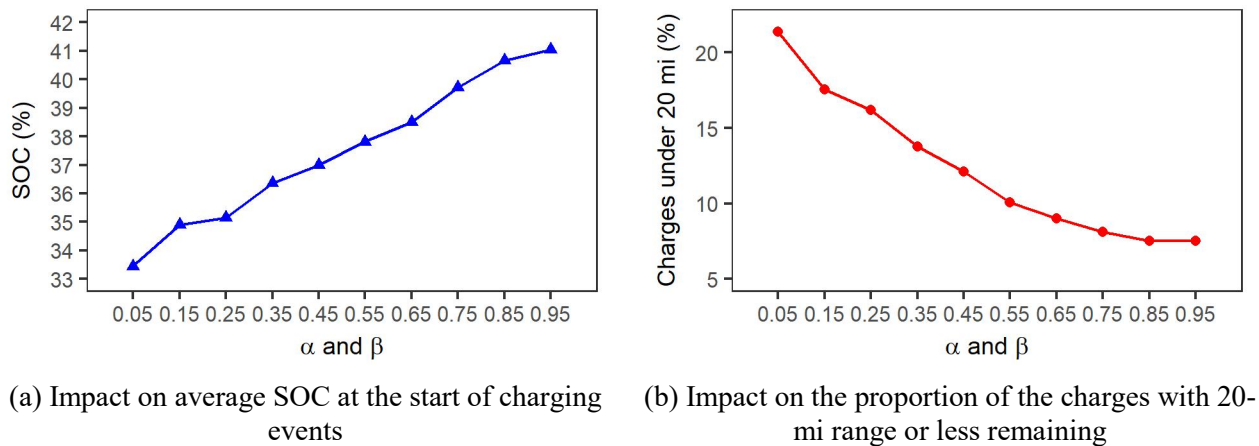


Figure 5.8 *Impacts of BEV drivers' risk preference on charging behavior.*

λ has relatively weaker impacts on charging behavior compared to α and β in the value function. In Figure 5.9, the values of λ vary from 1.25 to 5.75. Higher values of λ indicate an increasing degree of sensitivity to losses. As BEV drivers become more sensitive to losses than gains, the drivers exhibit stronger range anxiety, and the average battery SOC at the start of charging increases slightly. In the meantime, the proportion of the charges with 20 miles or less remaining is nearly unchanged.

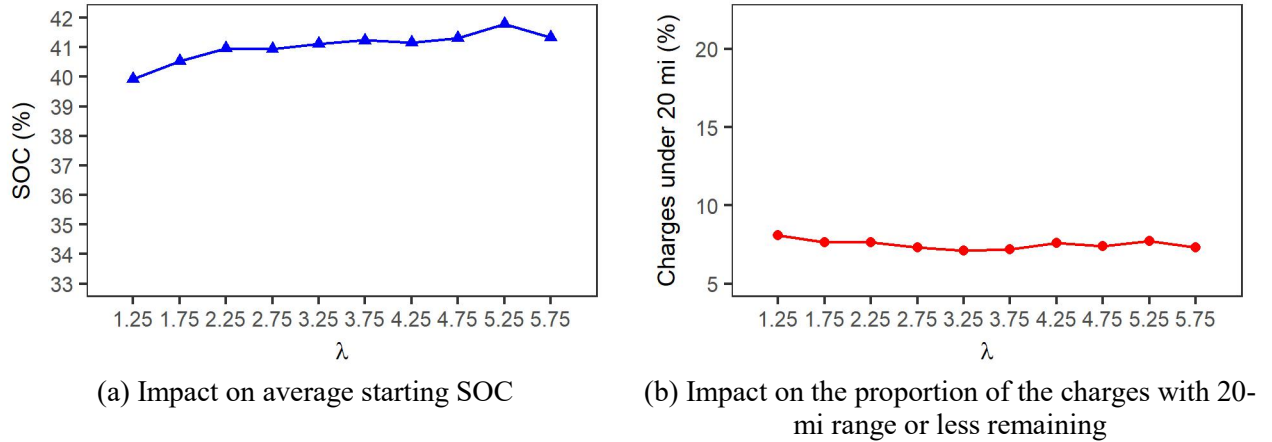


Figure 5.9 Impacts of BEV drivers' loss aversion attitude on charging behavior.

5.4.3. Impacts of Irrational Behavior on Charging Power Demand

The CPT parameters α , β , λ , γ , and δ control the degree of irrationality of decision makers. If these parameters all equal 1, BEV drivers are assumed to be rational when making charging decisions; that is, the drivers are neither risk averse nor risk seeking, losses and gains are weighted the same, and unlikely and likely outcomes are weighted the same. Figure 5.10 compares the charging power demand with the CPT model and the rational driver assumption. It is seen that the peak power demand with the rational driver assumption is underestimated by 4%. This could lead to insufficient expansion of grid capacity in the future. Figure 10 also compares the charging power demand if BEV drivers are highly risk averse (i.e., $\alpha, \beta = 0.95$) or highly risk seeking (i.e., $\alpha, \beta = 0.05$). The power demands of extremely risk-averse drivers are higher during evening peak hours than is shown in the CPT model, because these drivers are more worried about using up the battery range. By contrast, the strong risk-seeking drivers are less worried and tend to have lower charging demands. In summary, the CPT model, which captures the irrational behavior of BEV drivers, is more appropriate to guide grid capacity expansion choices. In addition, BEV drivers with different levels of irrationality have different effects on charging power demand.

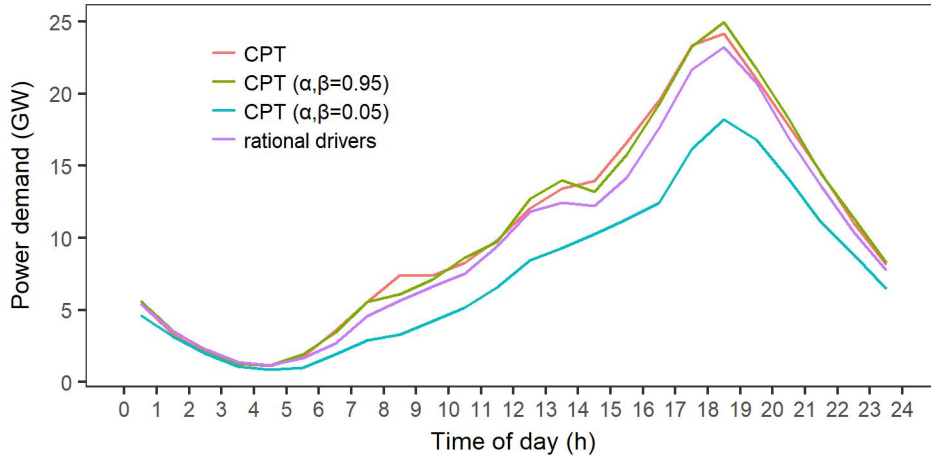


Figure 5.10 Charging power demand under the BEV mass-market scenario with drivers of different levels of irrationality.

5.4.4. Impacts of Public Charger Network Coverage on Charging Behavior

Public chargers provide charging opportunities when needed during the day. Higher public charger coverage also makes drivers more confident about accessing the greater range of charger potential (Nicholas and Tal, 2017). Figure 5.11 shows how public charger coverage affects charging location choices and power demand. It is seen that as the public charger coverage increases, drivers are more likely to use public chargers. About 20% of vehicles charge at public locations when the charger coverage exceeds 0.6. However, home charging still plays the dominant role and accounts for 63% of all charging events even if public charging opportunities are everywhere.

The charging power demand from public chargers increases significantly with the expansion of public charger network. Under the mass-market scenario where public charger coverage is assumed as 0.5, 36% of power demand comes from public chargers. Just 20% of charges done at public locations could potentially account for up to 40% of total electricity demand. In addition, expanding the grid capacity for public chargers is necessary as fast chargers will have a greater impact on the grid. Currently, the largest share of the power

demand still comes from homes. Thus, providing enough grid capacity in residential areas and maintaining reliable home charging service are important to expanded BEV use.

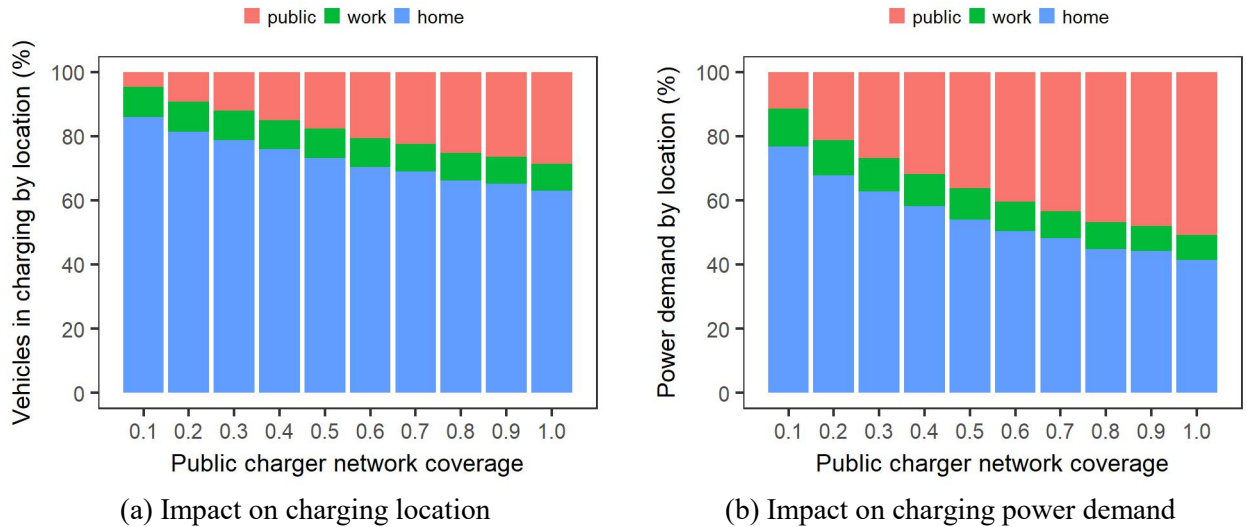


Figure 5.11 *Impacts of public charger network coverage on charging location and charging power demand.*

5.4.5. Impacts of Time-of-use Electricity Rate

The electricity price is assumed as constant in the previous sections. The time-of-use electricity rates, which vary with the changes in grid loads, have been implemented in some areas and will impact BEV drivers' charging behavior. Cao et al. (2016) defined 11 a.m. to 2 p.m. and 7 p.m. to 11 p.m. as the mid-peak period, 2 p.m. to 9 p.m. as the on-peak period, and 11 p.m. to 11 a.m. as the off-peak period. The on-peak rate is about 1.5 times of the mid-peak rate; the mid-peak rate is about twice of the off-peak rate (Cao et al., 2012; Cao et al., 2016; Crow, 2014). This TOU pricing is showed as the TOU 1 in Figure 5.12, where e_c is used as the mid-peak electricity price. The TOU 2, which increases the on-peak rate and reduces the off-peak rate, is used to explore drivers' response given a larger gap between on-peak and off-peak rates. Moreover, TOU pricing could also be determined by the charging power demands of BEVs. In Figure 5.7, the day's power demand is highest from 4 to 9 p.m.

and drops to the lowest level from 12 a.m. Thus, we can adjust TOU pricing accordingly, which might reduce additional peak demand. The TOU 3 and TOU 4 represent the pricing adjusted by the power demand of BEVs and have the same rates with the TOU 1 and TOU 2, respectively.

To take advantage of the off-peak electricity price, delayed charging is allowed for vehicles that satisfy the conditions that (1) home is the last destination of the day and (2) vehicles can be fully charged before the next trip. The charging start time will be postponed until a period of cheaper charging cost arrives. When BEV drivers return home and make their charging decisions, the cheaper electricity cost may change their charging choice and the power demand profile.

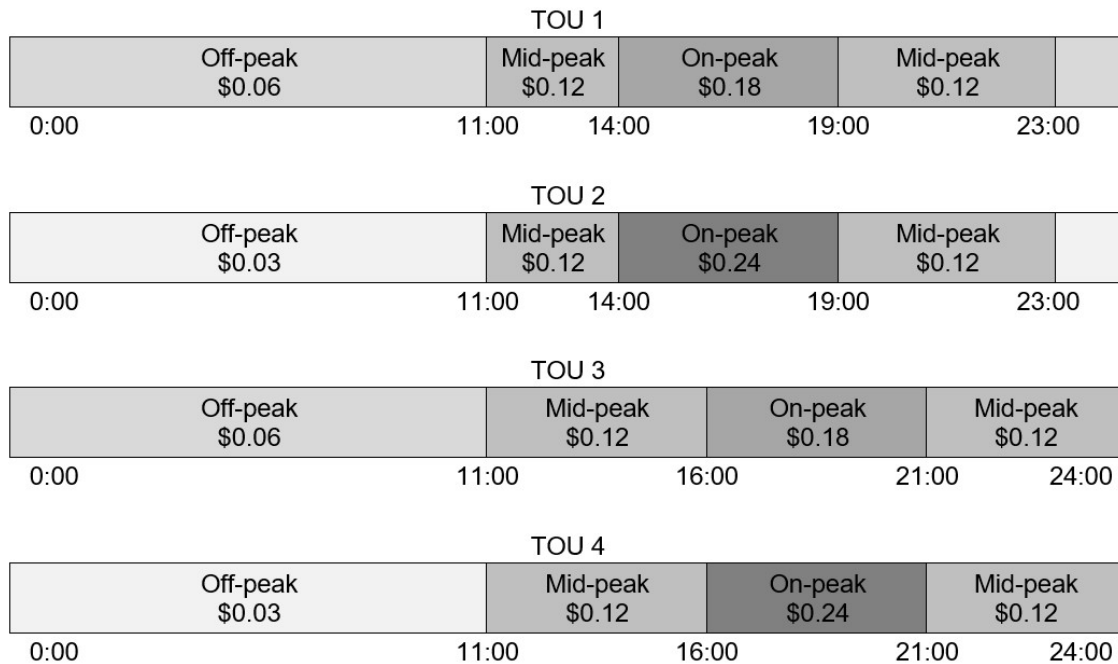


Figure 5.12 Time-of-use electricity rates (unit: \$/kWh).

Figure 5.13 compares the charging power demand with the constant rate and the four TOU rates under the BEV mass-market scenario. With TOU rates and delayed charging, the demand profiles become much flatter. The peak power demand decreases dramatically,

especially with the TOU 4 that cuts the peak demand at 6 to 7 p.m. by almost 50%. The evening peak loads shift to the off-peak period when the demand is very low with the constant rate. With more vehicles being fully charged overnight, the TOU-rate charging demand declines gradually until 7 a.m., but is still significantly higher than the constant-rate demand. Therefore, TOU rates with delayed charging help distribute the charging power demand more evenly throughout the day and have fewer negative impacts on the grid.

By adjusting TOU pricing based on the charging demands of BEVs, TOU 3 and 4 are able to reduce peak demand by more than TOU 1 and 2 are. The TOU 2 and 4 options, with a larger gap between on-peak and off-peak rates, reduce peak demand slightly and shift more peak demand to off-peak hours than do TOU 1 and 3. Therefore, the negative impacts of charging on the grid could be mitigated by adjusting TOU pricing based on the constant-rate power demand of BEVs.

Overall, cheaper charging costs may affect BEV drivers' charging decisions. The TOU electricity rate with delayed charging dramatically shifts the peak charging power demand to off-peak hours, especially from midnight to early morning.

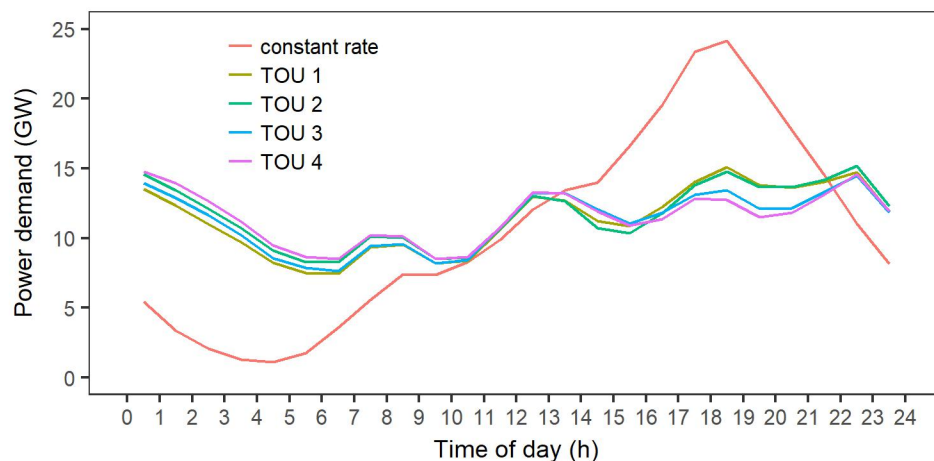


Figure 5.13 Charging power demand under the BEV mass-market scenario with different electricity rates.

5.5. Conclusions and Discussions

This chapter proposes a CPT-based modeling framework to describe the charging behavior of BEV drivers. The cost functions are introduced to convert the amount of range remaining at the next charger into the outcomes in the CPT model. BEV drivers decide to charge their vehicles according to the cumulative prospect values. Based on the 2017 NHTS, a BEV mass-market scenario is constructed to represent a mature BEV market in the long term—high market penetration of BEVs, long range, and extensive charging infrastructure. Under the mass-market scenario, this chapter applies the CPT model to study charging behavior and its collective effects on the power grid, including battery SOC at the start of charging events, charging timing and location, and charging power demand. In addition, sensitivity analyses with regard to the risk attitude parameters in the CPT model were conducted. Risk preference parameters α and β have significant impacts on charging behavior, while the loss aversion parameter λ does not. The results show that as BEV drivers display a higher degree of risk-seeking, they tend to charge vehicles at lower SOC levels and a higher proportion of charges start with less than 20 miles of remaining range.

The key findings are as follows. On average, BEV drivers charge their vehicles at 41% SOC. Most charges start with 40~50% SOC. Seventy-three percent of charging events start with less than 50% SOC and 7.5% engage in risky charging with less than 20 miles range remaining. BEV drivers are less likely to charge in the morning, and this type of charging mainly occurs at workplaces. The number of BEVs being charged and the electricity demand reach their peaks in the early evening. The public fast chargers contribute the most significant share of power demand during the daytime. During nighttime, the charging load mainly comes from home charging. Furthermore, we examine the collective effects of public charger network coverage on charging behavior and the power grid. Some

of the home charging shifts to charging at the workplace and public spots as the public charger network expands, but home charging still plays the dominant role in BEV charging and contributes the largest share to the power load. The power demand from the public chargers increases significantly with their expansion and has large effects on the grid. Finally, the TOU electricity rate and delayed charging greatly change the charging load profile under the BEV mass-market scenario. The peak charging power demands dramatically shift to off-peak hours from midnight to early morning. If we adjust the TOU pricing based on the charging demand under the constant rate, the charging loads could be distributed more evenly during the day and have fewer negative impacts on the grid. In addition, the proposed model can be used to provide insights to BEV use, charging infrastructure planning, and capacity expansion of the power grid.

One limitation of this research is the lack of behavioral data for calibrating the CPT model parameters. The model uses the experimental parameters set by Tversky and Kahneman (1992). In practice, the model parameters could vary across individuals due to different personalities and risk attitudes. Parameter calibration could be done in the future when charging behavior data are collected from a mature BEV market. Another limitation stems from the assumptions made for the mass-market scenario. This research makes reasonable assumptions based on previous studies regarding BEV market penetration and charger coverage in a mature market. However, BEV adoption and charging infrastructure development might take place faster than predicted.

CHAPTER 6. CONCLUSIONS, CONTRIBUTIONS AND FUTURE RESEARCH

This dissertation conducts data-driven analyses to the potential problems of future electric personal mobility, including the feasibility of electric taxis, dispatch of electric and autonomous taxis, and charging behavior of personal BEV drivers.

First, this dissertation studies the feasibility of BEVs based on the travel patterns of taxis. We extract ten variables from the trip data of the New York City yellow taxis to represent their spatial-temporal travel patterns in terms of driver-shift, travel demand and dwell, and examine the implications of these driving patterns on the BEV taxi feasibility. The BEV feasibility of a taxi is quantified as the percentage of occupied trips that can be completed by BEVs of a given driving range during a year. It is found that the currently deployed 280 public charging stations in New York City are far from sufficient to support a large BEV taxi fleet. However, adding merely 372 new charging stations at various locations where taxis frequently dwell can potentially make BEVs with 200- and 300-mile ranges feasible for more than half of the taxi fleet. The results also show that taxis with certain characteristics are more suitable for switching to BEV-200 or BEV-300, such as fewer daily shifts, fewer drivers assigned to the taxi, shorter daily driving distance, fewer daily dwells but longer dwelling time, and higher likelihood to dwell at the borough of Manhattan. This research contributes to the adoption of BEV taxis in the future. We can predict whether a gasoline taxi can be replaced by an electric taxi or not using their travel patterns, and the predictive model has high accuracy.

This research of BEV taxi feasibility could be improved by following these directions. The travel distance, travel time and speed of unoccupied trips are estimated based on the data of occupied trips. We can formulate more accurate estimation models. The

activity-based approach that quantifies the BEV taxi feasibility could take more realistic factors into account. For example, consider the driving distance to the nearest charging station during emergency charging, the travel distance from emergency charging station to the next customer, charging congestion due to limited public charging resources. Moreover, we must be cautious that the BEV taxi fleet can satisfy the same customer demand without following their original routes. The possible differences among the travel patterns of gasoline taxis and BEV taxis should be considered. This problem could be solved if trip data of real BEV taxis are collected in the future.

Second, this dissertation explores the potential of replacing current taxis with electric autonomous vehicles in New York City. A simulation framework for the operations of EAV taxis is designed, in which EAV taxis are dispatched by the optimization-based model and the neural network-based model. The optimization dispatch model aims at maximizing total rewards of picking up customers. The data of optimal dispatch solutions are generated by simulating EAV taxis that are dispatched by the optimization model. The neural network model is trained using the dispatch data to learn the optimal dispatch strategies. Although the dispatch decisions made by the neural network model are not optimal, the model has very close performance with the optimization dispatch model in terms of customer service and taxi operational efficiency. In addition, the neural network dispatch model is much faster to run. By comparing with the current taxis, it is found that the EAV taxis dispatched by the neural network model can improve operational efficiency by reducing empty travel distance. EAV taxis can also reduce fleet size by 15% while maintaining comparable level of service with the current taxi fleet and traveling shorter distance. This research is among only a few studies in EAV taxi operation modeling and the use of neural network for EAV taxi

dispatching. Instead of solving mathematical problems each time when dispatching taxis to customers, the neural network-based model can be much more efficient and thus more appropriate for real-time application.

We will extend this research by modeling EAV taxi charging and relocating. Instead of adopting deterministic charging rules, future research can schedule taxi charging ahead of time. EAV taxis will take advantage of more idle time for charging to prepare for serving in-advance peak demand. In addition, a relocating model could move EAV taxis from low-demand areas to high-demand areas and potentially save customers' waiting time. Moreover, when more computation resources are available, the simulation framework can simulate a larger EAV taxi fleet and generate more dispatch solution data for training the neural network.

Third, this dissertation proposes a cumulative prospect theory based modeling framework to describe the charging behavior of BEV drivers. CPT captures an individual's attitude and preference toward risk in the decision-making process. A BEV mass-market scenario is constructed using the 2017 National Household Travel Survey data. By applying the CPT-based charging behavior model, the dissertation studies the battery state-of-charge when drivers decide to charge their vehicles, charging timing and location choices, and charging power demand profile under the mass-market scenario. In addition, sensitivity analyses are used to examine the drivers' risk attitudes and public charger network coverage. BEV drivers who display a higher degree of risk-seeking tend to charge vehicles at a lower SOC. Some home charging shifts to workplace and public charging as the public charger network expands, but home charging still plays the most significant role in BEV use. The power demand from public chargers increases significantly with BEV expansion and has a

larger impact on the power grid. The time-of-use electricity rate can shift peak power demand to off-peak periods from midnight to early morning. This is the first research that models people's irrational decisions in charging electric vehicles. This is also one of the early studies that use the most recent NHTS data and reflect the newest travel characteristics of American people. Understanding BEV drivers' charging behavior will provide guidance to BEV use, charging infrastructure planning, and power grid capacity expansion.

Calibration of CPT model parameters could be done in the future when charging behavior data are collected from a mature BEV market. With different model parameters for different individuals, this research will explore the impact of various personalities and risk attitudes on charging behavior. This research also makes several assumptions regarding BEV market penetration and charger coverage in a mature market. With the wider adoption of electric vehicles and charging infrastructure, some assumptions will need to be adjusted.

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**APPENDIX. THE CPT-BASED CHARGING BEHAVIOR MODELING
FRAMEWORK PARAMETERS**

Table A.1 *The CPT-based charging behavior modeling framework parameters.*

Parameter	Value	Dollar year	Source	Adjusted value used in simulation
e_r	0.3 kWh/mile	—	U.S. EPA (2017)	—
r_a	20 miles	—	Franke and Krems (2013)	—
c_h	\$0.45 for personal local travel; \$0.85 for business local travel	2016	U.S. DOT (2016); Dong and Lin (2012); Wu et al. (2015); Wu et al. (2014)	\$0.46 for personal local travel; \$0.87 for business local travel
c_s	\$5	2015	Francfort (2015)	\$5.14
e_c	\$0.12/kWh	2017	U.S. EIA (2017)	\$0.12/kWh
c_p	\$109	2016	Moor (2016)	\$111.29
c_t	\$2.51/mile	2018	TaxiFareFinder (2018)	\$2.46/mile
α	0.88	—	Tversky and Kahneman (1992)	—
β	0.88	—		—
λ	2.25	—		—
γ	0.61	—		—
δ	0.69	—		—