Big Data for Urban Sustainability:

Integrating Personal Mobility Dynamics in Environmental Assessments

by

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DEDICATION

To my mom.

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LIST OF ABBREVIATIONS

ABM	Agent-based Models
AER	All-Electric Range
BEV	Battery Electric Vehicle
CNY	Chinese Yuan
CO	Carbon Monoxide
CO_2	Carbon Dioxide
EV	Electric Vehicle
EVI	Electric Vehicles Initiative
GHG	Greenhouse Gas
GPS	Global Positioning System
HEV	Hybrid Electric Vehicle
HOV	High-Occupancy Vehicle
ICE	Internal Combustion Engine
ICT	Information and Communication Technologies
KNN	K-Nearest-Neighbors
kWh	Kilowatt-Hour
MIP	Mixed Integer Problem
MIT	Massachusetts Institute of Technology
NHTS	National Household Travel Survey
NO_x	Nitrogen Oxide
NPV	Net Present Value
PHEV	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter
SO_2	Sulfate Dioxide

SOC	State of Charge
VMT	Vehicle-Miles-Travelled
VOC	Volatile Organic Compounds

ABSTRACT

To alleviate fossil fuel use, reduce air emissions, and mitigate climate change, "new mobility" systems start to emerge with technologies such as electric vehicles, multi-modal transportation enabled by information and communications technology, and car/ride sharing. Current literature on the environmental implications of these emerging systems is often limited by using aggregated travel pattern data to characterize personal mobility dynamics, neglecting the individual heterogeneity. Individual travel patterns affect several key factors that determine potential environmental impacts, including: charging behaviors, connection needs between different transportation modes, and car/ride sharing potentials. Therefore, to better understand these emerging systems and inform decision making, travel patterns at the individual level need to be taken into account in environmental assessments. Using vehicle trajectory data of over 10,000 taxis in Beijing, this research demonstrates the benefits of integrating individual travel patterns into environmental assessments through three case studies (vehicle electrification, charging station siting, and ride sharing) focusing on two emerging systems: electric vehicles and ride sharing. Results from the vehicle electrification case study show that individual travel patterns can impact the environmental performance of fleet electrification. When unit battery cost exceeds $200/kWh, vehicles with greater battery range cannot continuously improve travel electrification and may even reduce the overall electrification rate. At the current unit battery cost of $400/kWh, targeting subsidies to vehicles with battery range around 90 miles can achieve higher electrification rate. The public charging station siting case study demonstrates that individual travel patterns can better estimate charging demand and guide public charging

infrastructure development. Charging stations sited according to individual travel patterns can increase electrification rate by 59% to 88% compared to the existing sites. Lastly, results from the ride sharing case study indicate that trip details extracted from vehicle trajectory data enable dynamic ride sharing modeling. Shared taxi rides in Beijing can reduce total fleet travel distance and air emissions by 33% with 10-minute travel time deviation tolerance. Only minimal tolerance to travel time change (4 minutes) is needed from the riders to enable significant ride sharing (sharing 60% of the trips and saving 20% of travel distance). In summary, vehicle trajectory data can be integrated into environmental assessments to capture individual travel patterns and improve our understanding of the emerging transportation systems.

CHAPTER I

Introduction

1.1 Overview

Urban transportation systems contribute significantly to sustainability challenges such as fossil fuel consumption, air pollution, and greenhouse gas (GHG) emissions. To alleviate fossil fuel use, reduce air emissions, and mitigate climate change, “new mobility” systems have started to emerge with technologies such as electric vehicles, multi-modal transportation enabled by information and communications technology (ICT), logistics optimization platforms, and car/ride sharing [1, 2].

The current literature on assessing the environmental impacts of these emerging systems is often limited to the use of aggregated data to represent personal mobility dynamics such as national average annual (or daily) vehicle-miles-travelled (VMT). However, the environmental impacts of these emerging transportation systems are highly dependent on mobility dynamics at the individual level (e.g., how many miles one travels during a trip; how long one waits to take the next trip; and where people travel to and from). Taking electric vehicles (EV) as an example, individual travel patterns determine not only how much electricity is used but also whether base load or peak load electricity will be dispatched to charge the battery. Both factors affect the environmental performance of EVs significantly. Realizing how individual travel patterns can impact EV environmental performance, researchers have used travel survey data (e.g. National Household Travel Survey) to better model charging behaviors and energy consumption for EVs.

While travel survey data provide more detailed travel patterns compared to average values, the temporal coverage and spatial resolution of this type of data is low (discussed in more detail in **Section 2.2.1**). To draw conclusions at the fleet level and for particular cities, better characterization of travel patterns is needed. For the other emerging technologies, individual travel patterns also determine where connections are needed between different transportation modes and which trips can be shared. Therefore, to better understand the environmental implications of these emerging transportation systems, it is necessary to integrate personal mobility dynamics at the individual level into environmental assessments. This is the major motivation of this work.

The recent development of ICT has enabled several types of “big data” that can be used to study personal mobility dynamics at the individual level. Vehicle trajectory data collected by global positioning system (GPS) devices are particularly useful for environmental assessments of emerging transportation systems. This research aims to demonstrate the benefits of incorporating individual travel patterns into environmental assessments using vehicle trajectory data. Such integration can provide more realistic modeling of system performance and better support decision making to improve the sustainability of urban transportation. The contribution of this research is twofold. First, it presents a framework of integrating big data-informed travel patterns into environmental assessments. Second, each case study in this research also has its own real-world policy implications.

1.2 Research Questions

This research includes three case studies focusing on two emerging transportation systems: EV and ride sharing. These systems were chosen because they represent promising opportunities to improve transportation sustainability and have received increasing attention and policy support in many countries. Vehicle trajectory data of the taxi fleet in Beijing, China are used in all cases, but each case study used a separate data set because more recent data were made accessible as the study progressed. All three data sets contain the same type of data in the same formats; cover a similar number of vehicles; and are collected through the same process. Details of each data set are included in the data section in Chapter III to V. The scope and specific research questions for each case are summarized below.

Case 1: Implications of EV adoption on GHG emissions (Chapter III)

This case examines how individual travel patterns can affect potential environmental impacts of fleet electrification through EV adoption and utilization. Compared to previous studies which assume that everyone follows the same travel pattern as the aggregated average and neglect the heterogeneity of individual users, this case study not only uses real-world trajectory data to better model individual EV utilization, but also includes an adoption model to reflect the fact that not all drivers can benefit from EV adoption. Specifically, I addressed the following technical, policy, and environmental questions:

1) Based on individual travel patterns, what percentage of fleet travel can be electrified?

2) What is the optimal battery range to achieve the highest level of travel electrification?

3) How can the government promote electric vehicles more cost effectively?

4) What are the associated GHG emission impacts of taxi fleet electrification in Beijing?

Case 2: Public charging station siting based on individual travel demands (Chapter IV)

The environmental performance of EV systems is highly dependent on the charging infrastructure, which determines charging availability and behavior. This case examines the benefit of using big data-informed travel patterns for EV charging infrastructure development. Current literature of charging infrastructure siting has two research gaps: inappropriate estimation of charging demand and the lack of environmental consideration in the models. This case study addresses both gaps by using real world travel pattern data to better represent charging demand and developing an optimization model to site charging stations for maximum environmental benefits. The research questions are:

1) How do spatial locations of charging stations impact the electrification rate?

2) How should public charging stations be sited to maximize potential environmental benefits?

Case 3: Environmental benefits of ride sharing (Chapter V)

This case demonstrates how individual travel patterns can improve understanding of the environmental benefits of ride sharing. While recent ICT development provides unprecedented opportunities for dynamic ride sharing at the large scale, the environmental benefits of implementing such ride sharing system in urban cities are not yet quantified. This case study evaluates the environmental benefits of shared taxis at the city scale. The specific research questions include:

1) How many VMT can be reduced from implementing shared taxis in Beijing?

2) How much air emissions can be reduced from implementing ride sharing?

1.3 Structure of the Dissertation

The remainder of the dissertation is organized as follows. Chapter II reviews relevant literatures and identifies research gaps. Chapters III to V present three cases of integrating big data-informed individual travel patterns in evaluating the environmental implications of emerging transportation systems. The last chapter concludes and envisions future work.

Chapter III evaluates the GHG implications of electrifying the taxi fleet in Beijing. Taking a data-driven approach, plug-in hybrid electric vehicle adoption and utilization were modeled using real-time vehicle trajectory data of 10,375 taxis (18% of the fleet) in Beijing during one week. The impacts of government subsidy, battery range and cost, charging infrastructure availability, and electricity mix were also examined. The results have been published in *Environmental Science and Technology* (Vol.47, No.16, p.9035-9043) [3].

Chapter IV investigates how individual travel patterns can inform public charging station siting to maximize potential environmental benefits using vehicle trajectory data of 11,880 taxis in Beijing for three weeks. This chapter first demonstrates that public charging stations sited based on individual travel patterns can lead to higher travel electrification compared to the same number of charging stations in existing locations. An optimization model is then developed to identify the optimal charging station locations that can maximize electrified VMT at the fleet level. The first part of this chapter (**Section 4.3.1**) has been published in *Transportation Research Part D: Transport and Environment* (Vol.33, p.39-46) [4] and the second part (**Section 4.3.2**) has been submitted to the same journal.

Chapter V evaluates the environmental benefits of taxi ride sharing in Beijing. Passenger pick up and drop off locations are extracted from vehicle trajectory data of 12,083 taxis in Beijing for one month to identify which trips can be shared and how many VMT can be saved. The matching of the rides to be shared is determined by first identifying all sharable trips and then solving an optimization model to maximize saved VMT.

CHAPTER II

Literature Review

2.1 Environmental Implications of Emerging Transportation Systems

Transportation accounts for approximately 25% of the global energy demand and more than 62% of all the oil consumption [5]. In the U.S., transportation contributes 27% of the total energy use in 2013 [6]. In addition, over 92% of the transportation energy consumption is petroleum based [6], indicating a high dependence on oil of the U.S. transportation sector. In addition, the U.S. transportation sector is responsible for 28% of the GHG emissions [6]. Transportation also contributes to other air pollutants such as particulate matters (PM), carbon monoxide (CO), and volatile organic compounds (VOC) [7]. In the developing countries, on the other hand, the transportation sector undergoes rapid development. Passenger road transportation in China has increased by eight times during the past two decades [8]. Vehicle ownership is growing at a rate of 10.6% in China, 7% in India, and 6.5% in Indonesia each year [9]. Keshavarzian et al (2012). estimated that, by 2020, world oil demand of the road transportation sector will increase by over 30%, compared to the 2008 level in the business-as-usual case [10].

New technologies, such as EV, multi-modal transportation, connected and autonomous vehicles, and car/ride share, provide potential opportunities to improve urban transportation systems and mitigate climate change by reducing carbon emissions [1, 2]. EVs and ride sharing are two emerging transportation systems that have received ever greater attention in recent years. Currently many countries have policies to incentivize vehicle electrification; and 15 countries, including the U.S., United Kingdom, China, and India, have participated in the Electric Vehicles Initiative (EVI), which aims to deploy 20 million electric cars globally by 2020 [11]. Ride sharing, an old idea re-boosted by new technologies, has also become increasingly popular. Uber recently announced that half of the Uber rides in San Francisco are shared rides using UberPool service [12]. These emerging systems are often labelled as “green transportation”; however, their environmental impacts are still unclear.

2.1.1 Vehicle Electrification

Electric vehicles (EV) include hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV) [13]. EV is considered as a potential sustainable transportation option because it has two major advantages. First, using electricity from the grid as a transportation fuel can diversify fuel sources for the transportation sector. Unlike gasoline, electricity can be generated from various sources including renewable ones. Second, depending on whether PHEVs or BEVs are adopted, EV system can reduce or eliminate tailpipe emissions, presenting potential opportunities to reduce urban air pollution from road transportation. However, while EVs can reduce gasoline use, they increase the electricity consumption. Depending on how the electricity is generated, emissions of particular air pollutants may reduce or increase [14]. Therefore, to fully evaluate the environmental impacts of the EV system, life cycle assessment (LCA) is adopted to investigate the life cycle impacts of vehicle (and battery) production, fuel production, vehicle use, and end-of-life handling [15].

Many studies have evaluated the energy consumption [16-24], GHG emissions [18, 20, 22-30], and other criteria air pollutants [23, 27, 28, 31-33] of EV systems using LCA. However, as Hawkins et al. (2012) pointed out, the scope and model details of these studies are very different from one another, leading to highly variable results [15]. One major source of uncertainty Hawkins et al. (2012) identified is the electricity used to charge EVs [15], which is determined by vehicle fuel economy, electricity mix, and charging behavior. While the impacts of vehicle fuel economy and regional electricity mix on EV's environmental performance have been well recognized [14, 24], the impact of charging behavior is often overlooked.

Charging behavior can affect the environmental performances of EVs from the following three perspectives. First, charging behavior determines the amount of VMT that can be powered by electricity. For PHEVs which can use both electricity and liquid fuel, determining the fuel consumption allocation between electricity and liquid fuel (a.k.a., utility factor [34]) is critical in estimating the life cycle environmental impacts. On the other hand, for some BEVs, if a vehicle is able to charge between two trips, it will have enough energy to fulfill the second trip (assuming the trip is within the battery range). Otherwise, the driver will have to seek alternative transportation options.

Second, when EVs are plugged-in determines what types of fuel sources are used to generate the electricity used for charging. Many studies have argued that average grid emission factors can be misleading and marginal emissions factors should be used to calculate the electricity emission changes due to the adoption of new technologies [26, 35, 36].

Lastly, an EV user's travel pattern implies his or her potential charging behavior because the vehicle parking time and location represents potential charging opportunities. Users whose travel patterns allow them to benefit more from EVs are more likely to adopt [37]. Lack of economic competitiveness is one of the major barriers for EV adoption [38]. Given the fact that electricity is cheaper than liquid fuels on a per mile basis in most cases, EVs become a more viable option for those whose travel patterns and charging behaviors allow them driving more VMT on electricity [37].

However, in existing literature, most studies make rather simplified assumptions about the charging behaviors (e.g., charging once per day at night, or charging during specific hours [39]). This neglects the heterogeneity of individual travel needs and charging behaviors, leading to unrealistic estimation of the amount of VMT that can be electrified and the source of the electricity that will be used to charge EVs. This simplification is due to the use of aggregated travel pattern data (e.g., average annual/daily travel distance) traditionally used to study the environmental impacts of gasoline vehicles. Considering travel patterns at the individual level is necessary to better understand personal mobility dynamics, individual charging behaviors, and corresponding environmental impacts.

Another factor that can also influence charging behavior is the availability of charging infrastructure. Current literatures on environmental impacts of EVs focus mostly on home and work place charging and pay little attention to the potential contribution of public charging infrastructure [17, 22, 25, 39, 40]. Being able to charge outside of home is very important from the consumers' perspective and can significantly impact EV adoption. However, charging infrastructure alone will not determine its contribution to vehicle electrification in a city. It's the interaction between charging infrastructure and individual travel needs that matters the most. Charging stations built in locations with higher charging demand are more likely to be utilized and can support the EV system better. However, two research gaps exist in current studies on siting public charging stations: inappropriate estimation of charging demand and the lack of environmental consideration in optimization models. First, current studies use approaches similar to those used for estimating refueling demand to site gas stations, such as road traffic density

[41], distribution of gas stations [42], and vehicle ownership data [43-45], to estimate charging demand. Unlike refueling liquid fuels which only takes a few minutes to fill the tank, fully recharging the battery on an EV can take a much longer time, from 30 minutes to several hours, depending on the charger power, battery size, and the state of charge of the battery [46]. Therefore, EV charging is more likely to happen at the end of a trip instead of in the middle of a trip. Therefore, traffic volume does not necessarily correspond to charging demand. In addition, EV owners can charge their vehicles at home overnight, which means vehicle ownership density is not a good proxy for public charging demand either. As a result, to support better planning of public charging infrastructure, it is also necessary to consider individual travel patterns to better represent charging demand. Second, current siting models focus on minimizing costs or travel distance to charging stations [45, 47]. Few studies considered environmental impacts of EV charging as the objective function. The ultimate goal of EV system deployment is to meet more travel needs using electricity instead of fossil-based liquid fuels. Therefore, models that site charging stations to maximize environmental benefits can inform policy making for charging infrastructure development.

2.1.2 Ride Sharing

In the U.S., the average vehicle occupancy rate is 1.13 for commute and 1.67 for all trip purposes (shopping, recreational, etc.) [48]. Ride sharing, as a way to increase vehicle occupancy rate, can potentially reduce transportation energy consumption and alleviate traffic congestion. The idea of ride sharing is not new. As early as during World Word II, the U.S. government had organized ride sharing (Car-Sharing Club) to conserve fuel [49]. Other programs and policies, such as employer vanpool programs and High-Occupancy Vehicle (HOV) lanes, are also established to encourage ride sharing. Although ride sharing can provide benefits both to the society (e.g., reduce traffic and emissions) and the participants (e.g., save fuel and parking cost), due to the complexity in ride sharing arrangements and safety concerns of riding with strangers, ride sharing has been deployed only at a relatively small scale [49-51].

However, the recent wide adoption of smartphone and various applications (apps) has provided new opportunities for ride sharing at a larger scale. The GPS-enabled smartphone apps allow people to easily share their travel information, such as trip origin (or current location), trip destination, and desired departure and arrival time. Based on that information, a matching algorithm can then be developed to quickly identify matches and optimize supply-demand opportunities [52]. This dynamic ride sharing (a.k.a., real-time ride sharing) system only requires a minimal amount of lead-time, which overcomes the arrangement barrier. In addition, the involvement of social network and reputation systems in many apps help build trust and makes people feel more comfortable to share information and properties with strangers (e.g., Uber, Sidecar, Lyft, Airbnb) [53, 54]. This helps to overcome the psychological barrier of ride sharing. While ride sharing face unprecedented opportunities, it is still not clear how much a city can benefit from an environmental perspective. Understanding the environmental impacts of ride sharing and the key factors that determine the potential impacts can help inform policymaking to improve urban sustainability.

The current literature focuses on ride sharing on a small geographic scale [51], the characteristics of people who ride share [55, 56], and fast algorithms for ride matching and recommender system development [52, 57-61]. The environmental benefits of large-scale ride sharing are yet to be quantified. Jacobson and King (2009) pointed out that the fuel saving potential from ride sharing is largely dependent on the additional travel required to pick up additional passengers [62]. Therefore, knowing travel demands at the individual level is critical to assessing the environmental impacts of ride sharing.

2.2 Characterization of Individual Travel Patterns

Having recognized the importance of understanding personal mobility dynamics in different fields, different types of data are explored to characterize individual travel patterns.

2.2.1 Travel Survey Data

Travel surveys are conducted in many countries to understand national travel and transportation patterns. In the U.S., the National Household Travel Survey (NHTS) is conducted every five to eight years to compile an inventory of daily travels [63]. The most recent 2009 NHTS data collect daily travel data from 150,147 households selected randomly from landline telephone numbers. Each household is assigned a travel day (from 4:00am to 3:59am the following day) and reports on a travel dairy the start and end time of each trip taken in the day, purpose of the trip, transportation mode, and trip distances [64]. The NHTS data also include the demographic and vehicle ownership information of each surveyed household.

NHTS data at different aggregated levels are used to study the potential travel and charging behaviors of EVs (**Table 2-1**). At the most aggregated level, the daily vehicle travel distances from all trips are used to generate a frequency distribution curve of daily VMT. The portion of the travel where the daily VMT is less than the all-electric range of the EV can be considered substitutable by electricity (e.g., in [20, 25]). Mid-day charging at work places or public charging stations is not considered in these studies. At a less aggregated level, distribution of home arrival time of the last vehicle trip derived from NHTS data is used to estimate unconstrained and constrained EV charging at home (e.g., in [65]). At the most granular level, detailed trip chain information is used to estimate PHEV charging and energy use under different charring scenarios (e.g., home only versus home and work, and slow versus fast charging [34, 40, 66]). Although NHTS data provide very detailed information on daily trip chains (e.g., trip purpose, occupancy rate, demographics information), each household is surveyed for one day only. It is uncertain whether that assigned travel day represents a typical travel pattern for that household. Therefore, the day-to-day variation in travel patterns for each household cannot be assessed. Aggregating NHTS data at the regional or national data to obtain “typical” travel patterns assumes that every person has the same travel pattern as the aggregated average and may lead to unrealistic results [37]. In addition, because the travel diaries are self-reported, the accuracy of the information cannot be checked. Furthermore, the exact location of trip origins, destinations, and the routes taken for the trip cannot be accurately recorded in travel diaries, making it impossible to perform location-specific analysis such as ride sharing matches. Lastly, NHTS sample size at the local level is small, limiting the ability to use NHTS data to draw conclusions specific to individual cities [67].

Table 2-1. Summary of previous studies on environmental impacts of EVs

	EV Type	**Scope**	**Trip distance**	**Charging behavior**
Shen and Han (2013)	BEV	Energy use, GHG	Average fuel economy	Not considered
Ma et al. (2012)	BEV	GHG	Average fuel economy	Not considered
Wang et al. (2013)	BEV	Energy use, GHG, criteria pollutants	Average	Not considered
Huo etal. (2012)	BEV	GHG, criteria pollutants	Average fuel economy	Not considered
Huo et al. (2009)	BEV	Criteria pollutants	Average fuel economy	Not considered
Ji et al. (2011)	BEV, eBike	Criteria pollutants	Average fuel economy	Not considered
Tessum et al. (2014)	BEV	O_3, $PM_{2.5}$	Average fuel economy	NHTS trips

Smith (2010)	BEV	Energy use, CO_2	Simulated driving cycles	Not considered
Stephan and Sullivan (2007)	PHEV	Energy use, CO_2	Daily average	Night time spare
Samaras and Meisterling (2007)	PHEV	GHG	UHTS distribution	Once per day, fully charged
Elgowainy et al. (2013)	PHEV	Energy use, GHG	NHTS distribution	Once per day, fully charged
Graver et al. (2011)	PHEV	Energy use, CO_2, criteria pollutants	Tested driving cycles	Once per day, fully charged
Raykin et al. (2012)	PHEV	Energy use, GHG	Simulated driving cycles	Assumed full battery at beginning of each cycle
Marshall et al. (2013)	PEHV	Energy use, GHG, criteria pollutants	NHTS trips	Once daily upon arriving home
Peterson (2011)	PHEV	CO_2, SO_2, Nox	NHTS trips	Home/work/smart charging
Kelly et al. (2012)	PHEV	Utility factor, charging load	NHTS trips	Home/work charging

2.2.2 Emerging "Big Data" Applications in New Mobility

The rapid development of ICT provides unpreceded opportunities to study individual travel patterns. The broad adoption of smartphones and various location-enabled applications, GPS devices, and other location-tracked systems (e.g., smart bus cards) have significantly improved our ability to collect, store, and analyze large-scale datasets (a.k.a., "big data"), which enables studying personal mobility at a wide range of spatial and temporal scales [68]. These emerging big data are known to have the characteristics of "3Vs": volume (data size is large), variety (data types are various), and velocity (the data are generated at high frequency, such as every second, minute) [69]. Although there is no consensus in the definition of big data yet, it is believed that data complexity instead of data size is the determining factor for big data [70]. The data sets introduced in this section are considered as big data because they can be used to characterize complex behaviors of the underlying systems.

Common types of big data used to study personal mobility dynamics include mobile phone traces, GPS trajectories, smart transit card records, and geo-tagged social media. These data have been used in many fields such as epidemics [71, 72], urban planning [73], and genetics [74] to characterize human travel dynamics. For example, cellphone data are used to identify urban activity patterns [75] and infer land use patterns [76]; GPS trajectories of individuals and vehicles are analyzed to study emergency response after natural disasters [77] and detect social events [78]; and geo-tagged social media data are used to study urban growth boundaries [79] and quantify tourism [80]. Transportation research, specifically, has also benefited from these above-mentioned datasets. Mobile phone call data are used to develop origin-destination matrices [81], identify human mobility motifs [82], and identify road usage patterns [82]. GPS traces are used to model urban traffic [83], facilitate route planning [84, 85], and detect anomalous traffic patterns [86]. Bus smart card data are analyzed to identify commuting patterns [87, 88] and evaluate the performance of public transit systems [89]. Because most of these datasets are not originally designed or collected for travel pattern modeling, each type of data has its own advantages and drawbacks.

Mobile phone trace data are collected by mobile network carriers for billing and operational purposes. It records the date, time, phone number (anonymized) of each cellphone activity (making or receiving a phone call or text message), and the coordinates of the cellphone tower routing the communication [90]. Compared to travel survey data, mobile phone traces have a much larger sample size and a broader spatial and temporal coverage. In addition, because the data are routinely collected for business operation purposes, the data collection cost is low [67]. However, mobile phone trace data also have several drawbacks: 1) because data recording is only triggered by cellphone use, the travel activity happened between two phone activities are not captured; 2) only the location of the nearest cellphone tower is recorded instead of the exact location of the user, introducing spatial uncertainties; and 3) due to privacy concerns, these data normally do not contain any social-economic or demographic information associated with the cellphone users.

Geo-tagged social media data are publicly shared information (e.g., tweets, photos, check-ins) on different social media sites (e.g., Twitter, Facebook, Google+, Flickr, Foursquare) with location data (typically as GPS coordinates) associated. Depending on each social media site's policy, large scale social media data could be hard to obtain [91]. Most of the large scale geo-tagged social media data used for research are streamed from Twitter API [92]. Geo-tagged social media data normally also have a large sample size. Except for the geolocation data, the additional information carried in geo-tagged social media data vary significantly and require additional data mining to be useful. In contrast to cellphone traces, geo-tagged social media data contain the exact location of the users. Depending on what the users choose to share with the public, geo-tagged social media data may include social-economic, demographic, and social network information. However, because the data are proactively generated by the social media site users, travel information between two active posts can get lost. In addition, how users arrive at each location is largely unknown.

Smart transit card data record the travel information when the card holders use the transit systems which accept such smart transit cards. The data normally include card id (anonymized), transportation mode and route (e.g., bus versus subway), onboard- and off-stations and time. However, if the transit system has a flat rate scheme and one only needs to swipe the card when he or she gets on the buses/subways, only the onboard locations are collected [79]. The data are constrained to the specific transit transportation mode and may not reflect the exact trip origins and destinations, because card holders could walk, bike, take a taxi, or drive to/from the transit stations from/to their trip origins/destinations.

GPS traces data are location trajectories collected continuously (sampled every a few seconds or minutes) by GPS devices equipped on vehicles [37, 46, 93-95], bikes [85], or individuals [96, 97]. Because the data are collected passively and do not require active participation of the user, in contrast to other types of data mentioned above, GPS traces normally have finer granularity both spatially (more accurate location information) and temporally (high frequency of sampling) [95]. Because of the high sample rate, the route of travel can be easily inferred. However, because only location data are collected, GPS traces data normally do not contain any social-economic, demographic, or social network information about the users. Due to privacy concerns and the cost associated with data collection, the sample size of GPS traces for private vehicles or individuals are normally small (100 to 300 samples). But the sample size of GPS traces for public vehicles (e.g., taxis) is normally much larger, covering a large portion of the fleet or the entire fleet.

2.2.3 Data Types and Characteristics

The aforementioned data types are compared from the perspectives of sample size, demographic information availability, trip purpose, transportation mode, the accuracy of location data, route information, and spatial and temporal resolutions (**Table 2-2**). As the purpose of this research is to study individual travel patterns to better understand the environmental impacts of emerging transportation systems, the ideal dataset should have high spatiotemporal resolution, accurate location data, detailed route and transportation mode information (for driving), and large sample size to support fleet level conclusions. Based on these criteria, GPS traces of vehicles (a.k.a., vehicle trajectory data) are the most suitable. Although currently only public vehicle trajectory data are available at the large scale, the framework and methods developed using public fleet vehicle trajectory data will be readily applicable to private vehicles. In addition, studying the public vehicles itself is also meaningful because public fleets are likely to be early adopters of these new technologies [98].

Table 2-2. Comparison of different types of data used for travel pattern analysis.

Data		Sample size	Demo-graphic info	Trip purpose	Transpor-tation mode	Accuracy of location	Route info	Spatial-temporal resolution
Travel survey		Small	Yes	Yes	Yes	Low	No	Low
Big data	**Cellphone traces**	Large	No	No	No	Low	No	Medium
	Geotagged social media data	Large	Maybe	Maybe	Maybe	High	No	Medium
	Smart bus cards records	Large	No	No	Yes	High	Yes	Medium
	Vehicle trajectory data	Large	No	No	Yes	High	Yes	High

Vehicle trajectory data are collected by GPS devices equipped on vehicles. It includes car id (anonymized), a time stamp of when the data point is recorded, the location of the vehicle in longitude and latitude at the time of recording, and the speed and direction of the vehicle (**Table 2-3**). Currently, most of the available vehicle trajectory data are for taxis, so some datasets also include the status of the vehicle (occupied or unoccupied).

Table 2-3. A sample set of vehicle trajectory data.

CARID	TIME	LONGITUDE	LATITUDE	SPEED	CAR STATUS	DIRECTION
806910942721	3/2/2009 9:24	116.37529	39.82684	0	0	0
806466435796	3/2/2009 9:24	116.12856	39.94698	0	0	357
806466446011	3/2/2009 9:24	116.41796	39.98082	0	0	0
806436736335	3/2/2009 9:24	116.46572	39.94891	61	0	345
806436741157	3/2/2009 9:22	116.42018	39.9548	0	1	0
806488638642	3/2/2009 9:24	116.32062	39.8887	11	1	267
….	….	….	….	….	….	….

Vehicle trajectory data can contain errors due to sensor noise or poor GPS signals (e.g., in cities with skyscrapers blocking the signals). In addition, for each vehicle, the raw data contain a series of points over time ($p_1 \rightarrow p_2 \rightarrow \ldots \rightarrow p_n$). The trip origins, destinations, travel distances, and staying points and durations need to be inferred from the raw data. Therefore, data cleaning and processing are required before vehicle trajectory data can be used for analysis [99, 100]. After cleaning, some studies separate vehicle trajectory data into trip chains (a series of driving and parking events) (e.g., in [37, 95]), while others retain more of the travel details (e.g., in [86, 101]).

2.4 Summary

With many emerging transportation systems (e.g., electric vehicles and ride sharing) offering opportunities to improve the sustainability of urban transportation, the environmental implications of these emerging systems are not well understood. Considering individual travel patterns is crucial to the evaluation of these environmental implications. Large-scale datasets made available by the recent ICT development offer unprecedented opportunities to study individual travel patterns. Among all available data types, vehicle trajectory data are the most suitable for environmental assessments of emerging transportation systems.

CHAPTER III

Greenhouse Gas Implications of Taxi Fleet Electrification

3.1 Introduction

Fossil fuel-based transportation contributes significantly to global GHG emissions and urban air pollution [102]. Fleet electrification through either PHEVs or BEVs is widely considered as a promising alternative to reduce the dependence on fossil fuels, mitigate GHG emissions, and improve air quality in urban areas. While PHEV/BEV technology develops rapidly in recent years, there exist great uncertainties in terms of market acceptance. Previous studies evaluated factors that impact PHEV/BEV adoption, including infrastructure support, economies of scale, word of mouth effects (influence from other people's perception of EVs), age of current vehicle, consumer income, and travel patterns [40, 103-110].

In particular, consumer travel patterns (i.e., travel behavior) have increasingly received significant attentions, because they directly determine whether PHEV/BEV is acceptable to consumers and how it is utilized for daily travels [37, 94, 111]. However, previous research has predominately used aggregated travel pattern data [34, 40], such as the often cited National Household Travel Survey (NHTS), which assumes that everyone follows the same travel pattern as the aggregated average and neglects the heterogeneity of individual users and their specific travel patterns. Recent attempts to differentiate the impacts of individual travel patterns on PHEV/BEV market acceptance have also been constrained by the size of travel pattern samples (usually in the dozens or hundreds) [37, 94] due to the difficulty in collecting travel behavior data from the private fleet.

Fortunately, the rapid development of ICT has increasingly made massive amount of travel behavior data available at a much larger scale. The availability of these “big data” (commonly referring to large-scale datasets [112]) on individual travel patterns, especially for public fleets, represents untapped opportunities to better understand how individual travel behavior affects the PHEV/BEV market acceptance and the associated environmental impacts.

This research examines a large-scale dataset containing real-time trajectories of 10,375 taxis in Beijing for one week [93, 113, 114] to explore the impacts of individual travel patterns on PHEV acceptance and associated GHG emission implications. Public fleets such as taxis, city buses, and government fleets, are likely to be early EV adopters in China [98]. Given that this dataset represents approximately 15% of Beijing’s taxi fleet, the results provide useful information on the feasibility and environmental implications of fleet electrification, which is promoted by the Chinese government in large cities [115]. More generally, the method of this study is applicable to other cities for which similar data are available. This research represents the first of a series of studies exploring the role of big data in environmental systems analysis for the emerging PHEV/BEV systems.

3.2 Data and Methods

3.2.1 Data

The dataset used in this study contains real-time trajectories of 10,357 taxis in Beijing over one week (February 2 to 8, 2008). The data were retrieved using global positioning system

(GPS) devices installed in taxis [93, 113]. Each trajectory data point includes a unique taxi ID, the time (to the seconds) of recording, and the position (longitude and latitude) of the taxi at the specific time. Depending on the GPS device settings in each vehicle, the frequency of recording ranges from five seconds to ten minutes, but stays consistent for the same vehicle. To clean up the raw data, I applied a filter to eliminate 1) empty data points, 2) duplicate data points, 3) taxis with less than seven data points, and 4) unreasonable off-the-chart locations. The weather condition during the week was mostly sunny and cloudy, with high temperature ranged from 0 to 2°C (32 to 36 °F), low temperature ranged from -8 to -6°C (18 to 20°F), and no precipitation (typical February weather for Beijing) [116-119]. The sixth day of the week (February 7^{th}) was the New Year's Day based on the lunar calendar, a Chinese national holiday. The impact of the holiday and weather condition on the results is analyzed in the sensitivity analysis and also discussed in the limitation section (**Section 3.3.8**). The dataset includes data from multiple taxi companies. Taxi companies in China provide universal services throughout the city. So there are no service territories for each taxi company.

3.2.2 Driving Segments and Charging Opportunities

Taxis are different from private vehicles in the way that taxis do not have uniformly regular parking time. Some taxi drivers take evening and late night shifts; some choose to pick up early morning businesses; and some drivers pair up to drive the same taxi in rotation to minimize costs. Therefore, "daily driving distance" is not a good metric to characterize taxi trips, because taxis may have significantly different starting and ending time of each "day"; and the length of a "day" may also be different from taxi to taxi (e.g., one-driver taxi versus two-driver taxi).

To address this issue, I introduce the concept of "driving segments." A driving segment is the total distance driven between two major resting periods when the vehicle is parked with a predetermined duration threshold. One segment can contain several separate trips, similar to the "trip chains" used in previous studies [37]. The resting periods between driving segments represent potential charging opportunities.

In this study, I range the predetermined resting threshold from 30 minutes to eight hours to test the impact of charging opportunities on PHEVs adoption. For example, 4-hr segments mean that each segment contains trips between two resting periods of at least four hours each. In other words, charging opportunities are only available if the vehicles have a resting time of four hours or longer. In this chapter, I focus the discussion on two extreme cases: the "home-charging only" scenario and the "ubiquitous charging" scenario. The home-charging only scenario represents a relatively conservative case that vehicles can only be charged at home, thus requires longer resting period (eight hours in this study). On the other hand, the ubiquitous charging scenario represents an extremely optimistic case that public charging stations are ubiquitously available, allowing drivers to charge their vehicles as long as they have more than half an hour to rest.

3.2.3 Charging Algorithm

I developed a charging algorithm to model PHEV charging activities based on taxi trajectories (**Figure 3-1**). For each taxi (taxi *i*), based on the predetermined resting period (δ), the trajectory can be translated into a series of driving segments and resting periods in temporal sequences. At the beginning of each driving segment (segment *j*), the condition of the vehicle's battery is represented by a "state of charge" (SOC_j), which means the remaining capacity of the battery relative to the all-electric range (AER). The SOC_j depends on the battery size of the

PHEV, driving distance, and charging opportunities of all segments prior of segment *j*. “Battery size” in this study refers to vehicle on-road AER in miles, and PHEVs in this study utilize a serial configuration. Based on SOC_j and battery size, whether available battery electricity is able to cover the travel needs of the entire segment can then be decided. If the entire segment can be powered by electricity, the total distance driven in this segment (D_j) is added to the total electrified mileage of taxi *i* (E_i). The SOC is then updated with electricity consumed in this segment and available charging time during resting period *j*. If the available electricity is not enough to cover the entire driving segment, the battery will be entirely depleted and the remaining mileage will be fueled by gasoline. Because the battery has been depleted, the SOC at the beginning of the next driving segment *j*+1 (SOC_{j+1}) will depend on the available charging time in the resting period *j*. Then the same process goes for the next segment (segment *j*+1). When all segments are analyzed, the portion of the trips of taxi *i* that can be electrified if using a PHEV under given battery AER and charging opportunities can be computed.

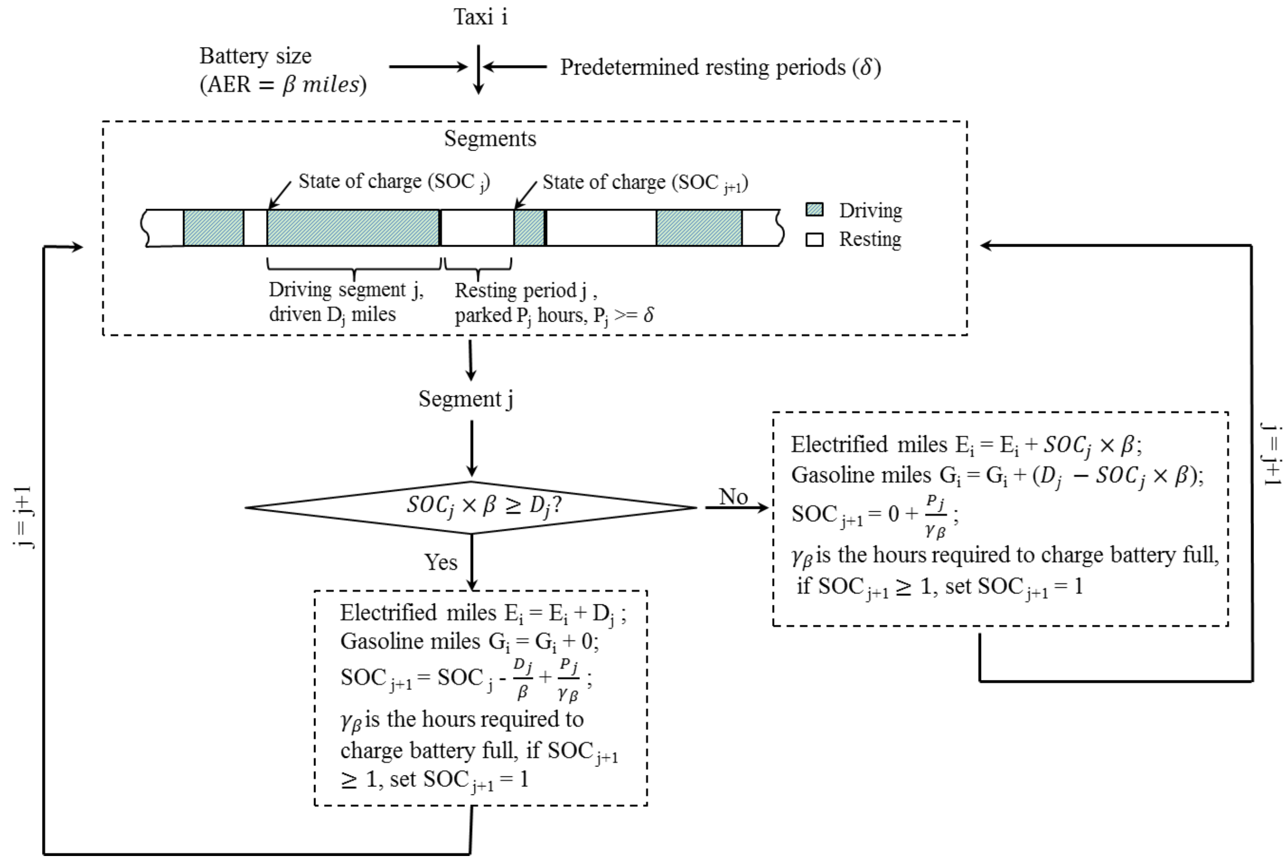

Figure 3-1. Charging algorithm for PHEVs.

3.2.4 Fuel Cost Saving and Electrification Rate

The main incentive for drivers to adopt PHEVs is the potential fuel cost savings, because electricity is cheaper than gasoline on a per VMT basis. To explore the heterogeneity of fuel cost saving potentials at the individual level, I calculated the probability distribution of fuel cost savings and payback time for the cost of batteries for Beijing's taxi fleet. Factors affecting fuel cost savings include gasoline cost, electricity cost, battery cost depending on battery size and unit price, fuel economy, charging opportunities, and charging speed (charging voltage, ampere, and battery size dependent).

In this study, I used the electricity price in 2012 of \$0.078/kWh (0.488 CNY/kWh), gasoline price of \$1.29/L (8.06 CNY/L), fuel economy at charge depleting mode of 0.35 kWh/mile (based on 2013 Volt) [120], fuel economy at charge sustaining mode of 35 mile/gal (city travel of 2013 Volt) [120], charging voltage at 240V, charging current at 16A [34], and charging efficiency of 88% [34]. The fuel economy of gasoline vehicles is assumed to be the same as in the PHEV charge sustaining mode (35 mile/gal). Currencies are converted based on an exchange rate of 6.23 CNY/USD. It is also assumed that all vehicles have a fully charged battery (SOC = 100%) at the beginning of the simulation. Battery size is measured by AER in miles, which is the maximum distance a fully charged vehicle can drive on electricity. I examined battery size ranging from 0 to 250 miles, battery cost from \$500/kWh (price at the time of the study) to \$100/kWh (future target) [121], and charging opportunity from “home-charging only” to “ubiquitous charging” to explore their impacts on fuel cost savings for individual vehicles and the overall electrification rate. This study simplifies the battery charging and discharging process with a linear change of SOC between 0% and 100%. I assumed that the price difference between a PHEV and a comparable conventional gasoline vehicle is solely due to the cost of the battery, which increases linearly with the battery’s capacity. To evaluate battery cost payback time, I used a discount rate of 5% to calculate the net present value (NPV) of future fuel cost savings. The impacts of these assumptions are tested by conducting a sensitivity analysis (**Section 3.3.7**).

3.2.5 PHEV Adoption

Previous studies based on the aggregated travel patterns (e.g. in [20, 25]) have an underlying assumption that the entire population will adopt PHEV. However, this assumption can lead to overestimation of electrification rates because the adoption rate is unlikely to be 100%

[37]. The cost of battery also plays a key role in PHEV adoption, because drivers who do not drive enough mileage to achieve payback of the battery cost within the vehicle life time are less likely to adopt PHEVs. In addition, drivers whose travel patterns allow few charging opportunities are also less likely to buy PHEVs or less likely to utilize PHEVs in charge depletion mode even if they adopt. Therefore, I used a payback model to allow drivers to adopt PHEVs only if they can payback the cost of batteries within eight years (regulated maximum service time of taxis in China [122]). If the payback time is longer than eight years, I assume that the driver will decline switching to PHEV and this taxi will stay as a conventional gasoline vehicle [37]. The utilization of PHEVs is modeled using the travel patterns detected for each individual vehicle. The fleet level VMT electrification rate is defined as the ratio of total electrified mileage to total mileage traveled.

The model is verified at both of the lower and upper boundaries. At the lower boundary, with extremely high battery cost and short payback time, no taxis adopt PHEVs and both of the adoption rate and electrification rate are zero. At the upper boundary, the parameters are relaxed to have zero battery cost, long payback time, and extremely large battery range to ensure that 100% adoption rate and electrification rate can be achieved.

3.2.6 Government Subsidy

I study two types of government subsidies in this research. The first is a one-time refund depending on the size of batteries. At the time of the study, the Chinese government offers a subsidy of $482/kWh (3,000 CNY/kWh) with a maximum per-vehicle ceiling at $8,026 (50,000 CNY) in total for PHEVs and $9,631 (60,000 CNY) for BEVs [123]. Several local governments (e.g., Shanghai) also offer an additional subsidy of $8,026 (50,000 CNY) for each PHEV. I examined the impact of government subsidy on fleet level VMT electrification with subsidies ranged from \$0 to \$803/kWh (5,000 CNY/kWh) with a cap of \$16,051 (100,000 CNY) per vehicle. The other subsidy type studied is the "electricity subsidy", meaning that the government subsidizes electricity to enlarge the fuel cost savings for PHEVs. The current electricity price is \$0.078/kWh (0.488 CNY/kWh) in Beijing. I studied electricity subsidy ranged between \$0 and \$0.064/kWh (0.4 CNY/kWh). I set the upper limit for government subsidy based on the rationale that if the drivers do not pay for electricity at all or even receive money from charging, their travel patterns might be significantly altered (e.g., drive more). I assumed that the electricity subsidy will be constant for eight years.

3.2.7 Greenhouse Gas Emissions

In general, PHEVs can eliminate or reduce tailpipe emissions but the life cycle GHG emissions may or may not decrease, depending on the electricity mix. The life cycle GHG emissions of a vehicle come from two parts: the vehicle cycle and the fuel cycle [124]. The vehicle cycle includes the production, operation, and end-of-life management of vehicles and batteries, while the fuel cycle includes the extraction, production, transportation, and consumption of the fuels.

GHG emissions associated with the production of a medium-sized passenger car in China is approximately 6,675 kg CO_2-eq/vehicle [125]. It is assumed that emissions associated with the manufacturing of PHEVs and conventional gasoline vehicles are identical, except that PHEVs need additional battery production. This assumption can be justified by the fact that smaller internal combustion engines (ICEs) in PHEVs can account for the difference due to electric motors and additional control equipment [25]. GHG emissions from the Li-ion battery production is approximately 120 kg CO_2-eq/kWh battery capacity [25]. The fuel cycle emissions are tightly tied to the carbon intensity of electricity production. China has six large power grids.

Beijing belongs to the North China Grid with a GHG emission factor of 236.7 g CO_2-eq/km traveled [126]. GHG emissions of conventional gasoline vehicles are approximately 224.4 g CO_2-eq/km [126]. Results obtained from the present dataset are scaled up to reflect total emissions of the entire taxi fleet electrified by PHEVs with different battery size. The change of electricity mix over time is not included in the modeling, but the potential impact of future electricity mix change is discussed.

3.3 Results and Discussion

3.3.1 Travel Patterns

The dataset after the filtration contains trajectories of 9,951 taxis with a total of 16.2 million data points and 7.7 million miles traveled. **Figure 3-2** provides an overview of the dataset by visualizing individual vehicle's average speed between sampling points. The black vertical bands represent the daily night-time parking. More than 60% of the taxis have over 1,000 data points. The predetermined resting periods used to define driving segments determine the distribution of distance traveled in each segment as well as the charging opportunities between segments (**Figure 3-3**). Segments with per-segment travel distance between 100 and 2,000 miles represent approximately 80% of the total VMT. Taxis gave people the impression that they are always in operation and would rarely park for an extended amount of time (e.g. 8 hours). Unexpectedly, the distribution of per-segment travel distance for 4-hour segments and 8-hour segments are quite similar. In particular, the distributions are almost identical between the 4-hourr and 8-hour segments when per-segment travel distance is between 50 and 100 miles (**Figure 3-3** insert). Using household vehicle travel data in Minnesota, Tamor et al. (2013)

observed similar results that if a vehicle has a charging opportunity for 4 hours, that charging opportunity is very likely to be over 8 hours as well [37].

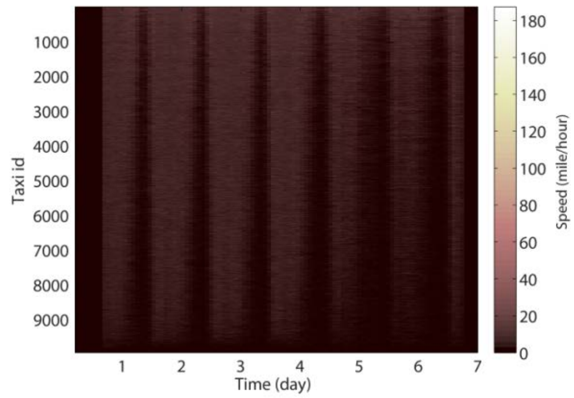

Figure 3-2. Average speed of each taxi based on the filtered dataset.

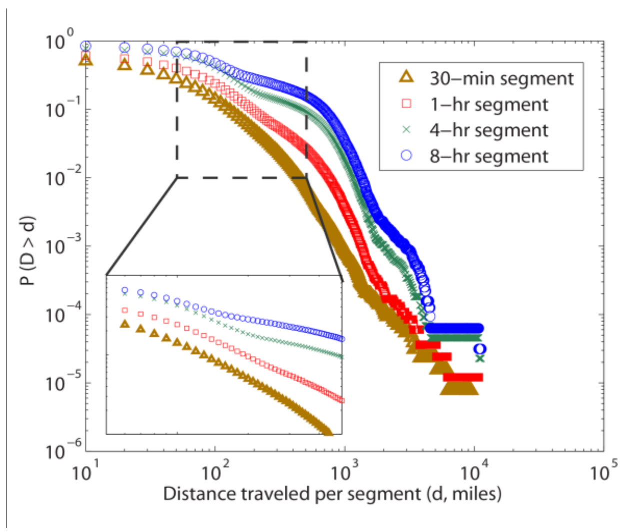

Figure 3-3. Complementary cumulative probability distribution of per-segment distance with different charging opportunities.

3.3.2 Fuel Cost Saving

Individual taxis with the same battery size can have very different fuel cost savings from adopting PHEVs, depending on different individual travel patterns. **Figure 3-4a** shows the complementary cumulative probability distribution of fuel cost savings from PHEV adoption, representing the probability of a randomly picked vehicle to have more fuel cost savings than the corresponding x-axis value. If the taxi fleet adopts PHEVs with 40-mile battery range (PHEV40), 90% of the taxis can save more than $5 per week while 10% of them can save more than $40 per week. When PHEVs with 240-mile battery range (PHEV240) are adopted by the fleet, 90% of the drivers can save more than $26 per week and 10% of them can save more than $79 per week.

Therefore, 90% of the taxis can save more than 5% of their fuel costs while 10% can save more than 57% with PHEV40. With PHEV240, 90% of the taxis can save at least 24% of the total fuel cost, while 35% can save at least 77% (**Figure 3-4a** insert). There is no correlation between absolute fuel cost savings and the percentage of total fuel cost reduction for individual taxis (**Figure 3-5**), indicating high variation in total fuel costs. The percent fuel cost saving that can be achieved by adopting PHEVs with large battery is significant. However, larger battery also increases upfront vehicle cost and therefore prolongs the payback time. **Figure 3-4b** presents the probability distribution of payback time for PHEVs with different battery sizes. At the time of the study, the unit battery cost is $500/kWh. It is notable that a significant portion of the vehicles (38% for PHEV40 and 99% for PHEV240) cannot compensate for the additional battery cost from their life time fuel savings at this cost. This indicates that fuel cost-saving itself is not enough to incentivize high PHEV adoption. Unit battery cost reduction can significantly shorten the payback time, especially for large batteries (**Figure 3-6**). Government subsidy also becomes critical in promoting PHEVs adoption at least at the early stage of market penetration.

3.3.3 Electrification Rate

To quantify fleet-level travel electrification, the ratio of total electrified VMT to the fleet's total VMT is defined as the electrification rate. The electrification rate is related to both PHEV battery size and unit cost of the battery, as presented in **Figure 3-4c**. When battery unit cost is relatively high ($300/kWh to $500/kWh), the overall electrification rate increases initially with the increased battery size but decreases after a tipping point. This result is interpreted as follows. When the battery unit cost is high, large batteries require high upfront vehicle premiums so that only few drivers with higher fuel cost-saving potentials can afford PHEVs. Where the electrification rate peaks represents the optimal battery size under each scenario. At current battery cost ($400/kWh), the optimal battery size is approximately 90 miles for this fleet. It is worth noting that the overall electrification rate stabilizes at around 40% when the battery unit cost is reduced to $200/kWh, indicating that battery cost is no longer a barrier to increase the electrification rate. Results in **Figure 3-4c** are based on ubiquitous charging scenario (30-min segments). When charging opportunity is limited to home-charging only, the same trend holds, but the overall electrification rate decreases (**Figure 3-4d**). These factors cannot be easily assessed using aggregated data and the electrification rate could be overestimated (**Figure 3-7**).

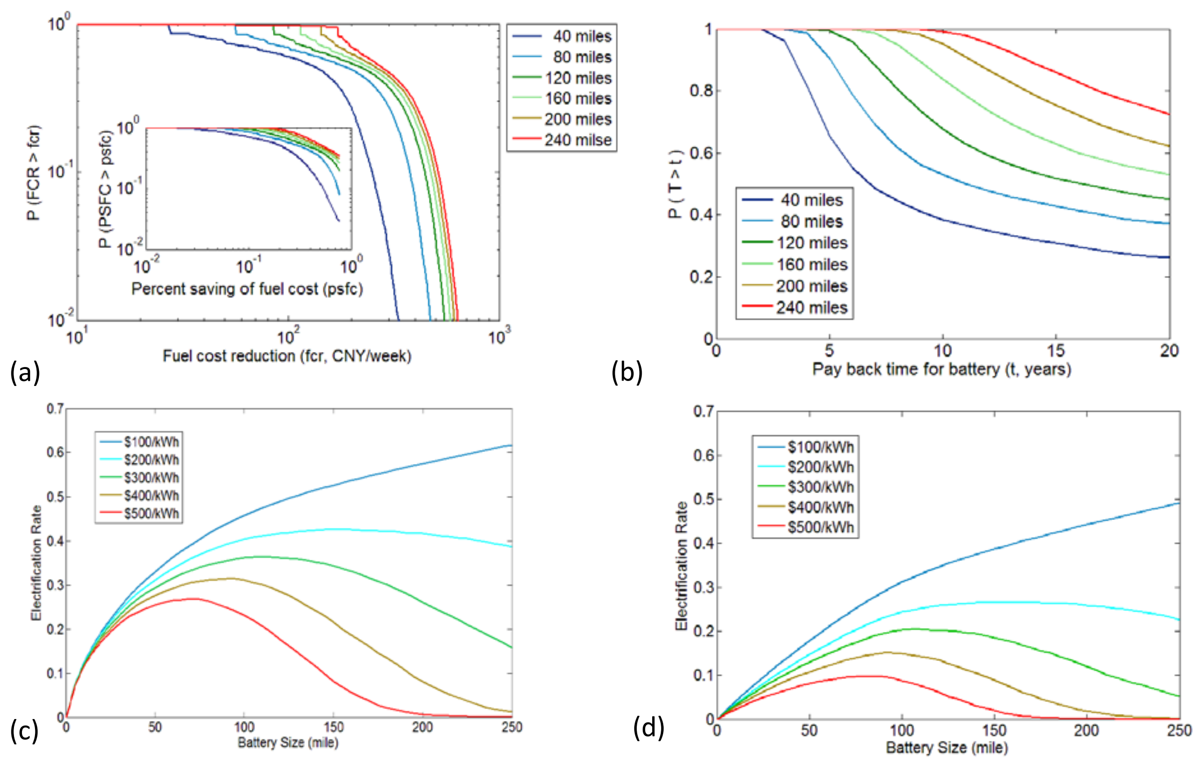

Figure 3-4. Fuel cost reduction, payback time, and electrification rate based on different vehicle battery ranges.
Note: a) Complementary cumulative probability distribution of weekly fuel cost saving with PHEVs regarding different battery sizes modeled with ubiquitous charging. Inserted graph shows percent saving of total fuel cost. b) Complementary cumulative probability distribution of payback time for PHEVs with different battery size modeled with ubiquitous charging and battery cost at $500/kWh. c) Electrification rates of total fleet VMT based on acceptance criteria of paying back battery cost within eight years for the ubiquitous charging scenario (charging opportunities exist when resting for longer than half an hour). d) Electrification rates of total fleet VMT based on acceptance criteria of paying back battery cost within eight years for home-charging only scenario (charging opportunities exist resting for longer than eight hours).

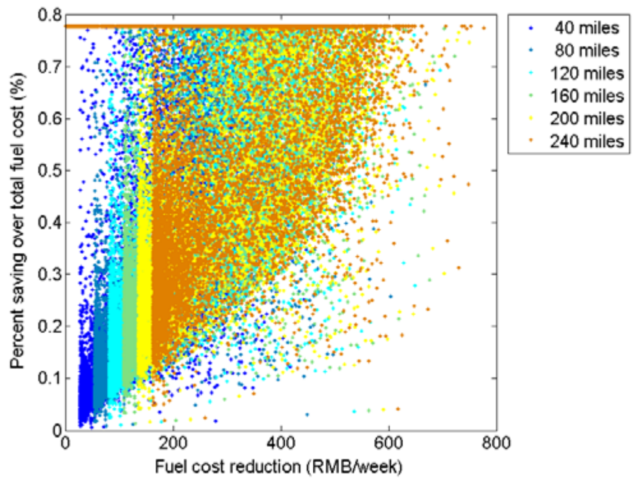

Figure 3-5. The relationship between percent saving and absolute fuel cost reduction.

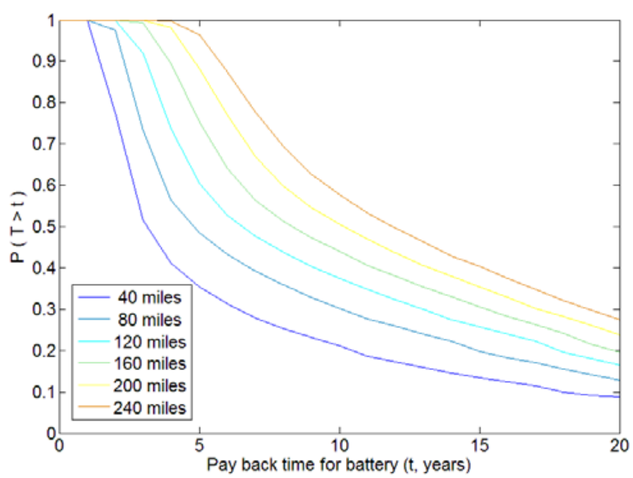

Figure 3-6. The complementary cumulative probability distribution of payback time with PHEVs regarding different battery sizes
Note: modeled with 30-min segments and battery cost at $250/kwh.

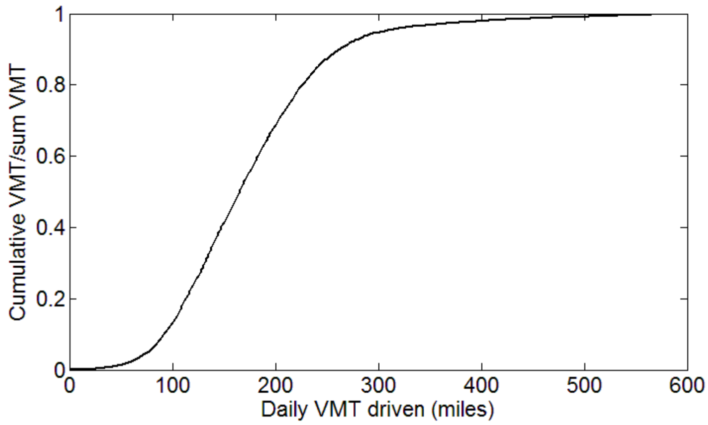

Figure 3-7. Aggregated daily VMT data of February 4, 2008.
Note: Estimating electrification rate based on aggregated daily VMT could lead to statement such as that "Taxis with daily VMT less than 150 miles drive 40% of total VMT. Therefore, 150-mile batteries could electrify 40% of total taxi VMT."

3.3.4 Impact of Subsidy

Government subsidy can significantly increase the fleet VMT electrification rate by offsetting high battery costs. **Figure 3-8a** shows that moderate government subsidy can increase overall electrification rate from 27% to as high as 45% with unit battery cost at $500/kWh. Similar to **Figure 3-4c**, tipping points can also be observed in **Figure 3-8a**, showing that the electrification rate first increases and then declines with increasing battery size if holding the government subsidy rate constant. **Figure 3-8a** also shows that, with the same battery size, a higher government subsidy rate only has marginal impacts on the electrification rate after reaching a threshold (dependent on battery size) due to the subsidy cap of $16,051 per vehicle.

In addition to a subsidy rate based on battery capacity, the total amount of subsidies is also relevant to policy making. The contour lines in **Figure 3-8a** represent the total government expenditures to subsidize the fleet electrification. It is interesting to note that the same amount of subsidies can achieve very different electrification results with different subsidy rates and battery sizes. **Figure 3-8a** suggests that PHEVs with battery size of 80 to 120 miles can potentially reach a maximal electrification rate of 45% with relatively low subsidies at a modest rate of $300 to $400/kWh. In the home-charging scenario, a modest government subsidy at $385/kWh is able to increase overall electrification rate from 10% to 31% **(**Figure 3-8**b).** When unit subsidy is above $385/kWh, electrification rate declines rapidly when battery size exceeds 115 miles. This is because the per-vehicle subsidy limit is reached and fuel cost savings required to breakeven with battery cost increase dramatically **(Figure 3-9)**.

Government can also incentivize PHEVs adoption and utilization by subsidizing electricity cost for charging or even providing free recharging [37, 127]. **Figure 3-8c** and **Figure 3-8d** show fleet VMT electrification with electricity subsidies up to $0.064/kWh (82% of the electricity price). I assumed that individual travel behavior does not change with electricity subsidies, which may underestimate the electrification rate if drivers actively seek charging opportunities. **Figure 3-8c** and **Figure 3-8d** also show that subsidizing electricity is less effective than subsidizing battery cost in promoting fleet electrification, but it is also relatively less expensive. If designed well, the same budget can achieve similar level of electrification rate with either subsidy option. The advantage of subsidizing electricity is that it requires substantially less money each year by spreading the financial investment over a longer period of time, while the purchasing subsidy requires greater upfront capital.

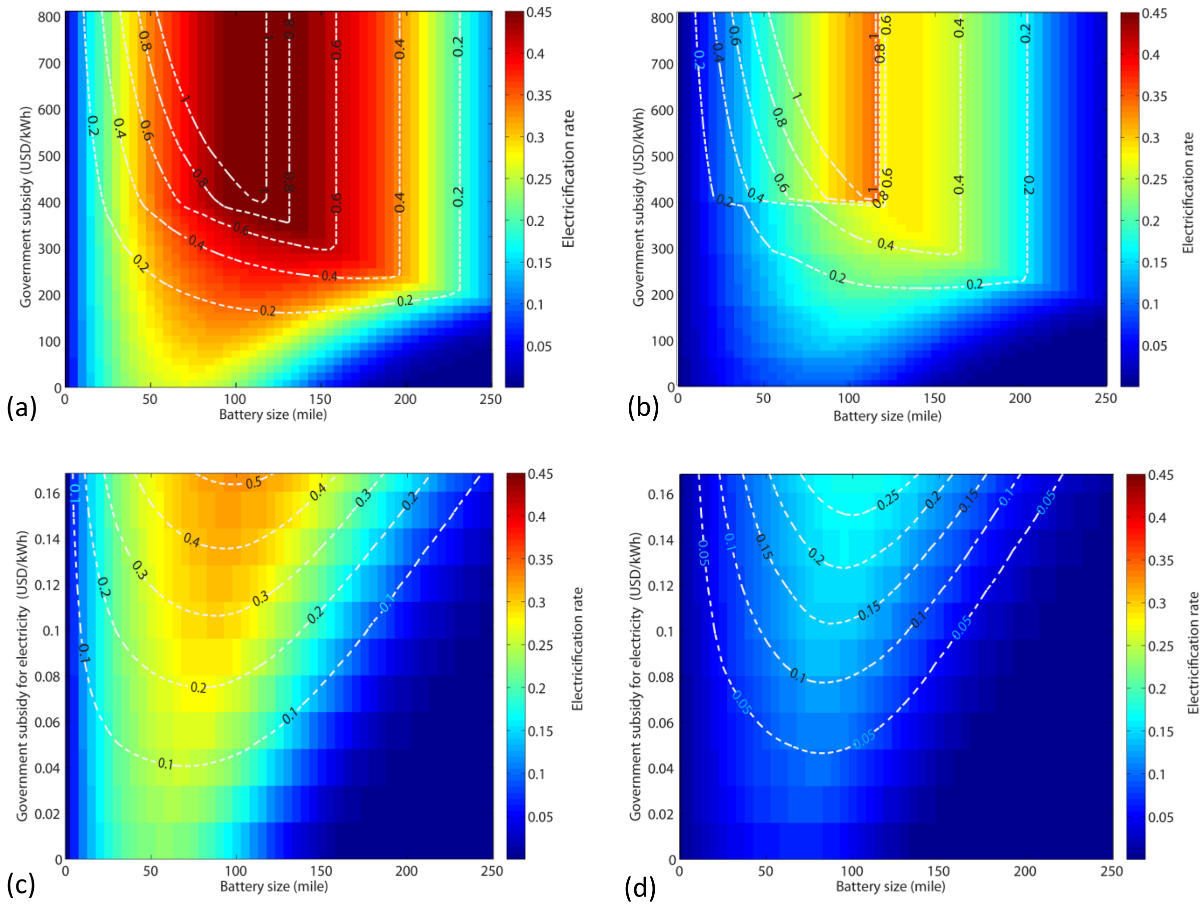

Figure 3-8. Impact of subsidies on fleet VMT electrification.
Note: One time purchasing subsidy from $0 to $803/kWh based on battery capacity with a maximum of $16,051 per vehicle and unit battery cost at $500/kWh under a) the ubiquitous charging scenario and b) the home-charging only scenario. Charging subsidy from $0 to $0.0644/kWh based on charged electricity for ten years under c) the ubiquitous charging scenario and d) the home-charging only scenario. Contour lines show total costs to government from subsidies in billion dollars.

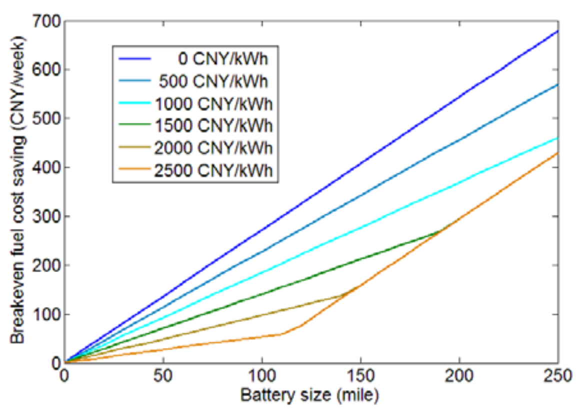

Figure 3-9. Minimum fuel cost saving required to payback battery cost under different purchasing subsidy scenarios. Note: modeled with battery cost at $500/kwh and payback time is ten years.

3.3.5 Impact on GHG Emissions

Previous research examines environmental implications of PHEVs adoption often on a per-vehicle or per-VMT basis, assuming specific battery size or VMT. This approach does not reflect the role of individual travel patterns and battery size variations in determining fleet electrification rate which in turn determines the environmental impacts. For example, considering two identical PHEVs with the same battery size and total annual VMT but different travel patterns, the vehicle that takes shorter trips between charging events tends to charge more often and can displace more gasoline than the other one which takes longer trips and has less frequent charging events. In addition, larger battery can electrify more VMT (**Figure 3-10**), but also implies more life cycle energy input, material use, and GHG emissions from the battery production. Can the GHG emission reduction from VMT electrification offset the emissions from battery production? **Figure 3-11a** shows that the marginal electrification rate, defined as the amount of VMT electrified per vehicle due to one mile of additional battery range, diminishes in general with increasing battery size. Note that government subsidy can actually reduce the marginal electrification rate by offering adoption incentives to vehicles that do not benefit much from PHEVs due to travel patterns. Similar to results showed in **Figure 3-4c** and **Figure 3-4d**, with current battery cost, limited public charging infrastructure, and no government subsidy, the greatest amount of gasoline displacement (1.1 million gallons per year) can be achieved by modest battery size (approximately 90 miles); larger batteries do not necessarily mean more VMT electrification or gasoline displacement (**Figure 3-11b**). The sudden drop of marginal electrification rate in the home-charging with subsidy scenario in **Figure 3-11a** (also in **b**, **c** and **d**) at around 120-mile battery size is due to the fact that the maximum per-vehicle subsidy ($16,051/vehicle) is reached, as explained earlier in discussing **Figure 3-8b**.

Given that electricity in China is largely produced from coal, especially in the northern region where Beijing is located, displacing ICE vehicles with electric vehicles can actually increase fuel cycle GHG emissions by 12.3 g CO_2-eq/km [126]. **Figure 3-11c** shows the life cycle emission changes of the fleet with PHEVs adoption and utilization modeled based on different battery sizes as described above. Because emissions in the fuel cycle dominate in the life cycle of a vehicle[128], life cycle GHG emissions increase and peak (at 38 kiloton CO_2-eq per year) without subsidies at around 80-mile battery range where the electrification rate is at the highest (**Figure 3-4c** and **Figure 3-4d**). With government subsidies, life cycle GHG emissions increase up to 115 kiloton CO_2-eq per year due to increased electrification rate. GHG reduction can be achieved if the electricity grid of Beijing becomes less carbon-intensive. Currently, Beijing is planning on decarbonizing its grid through measures such as increasing natural gas power generation, improving efficiency of existing plants, and diversifying fuel sources with renewables [129]. If the fuel cycle emission factor of electricity can be reduced to 168.7g/km (which can be achieved by replacing 40% coal with natural gas in electricity generation and increasing efficiency of coal-fired power plants by 10%), emission reduction of up to 36.5 kiloton CO_2-eq per year can be achieved (**Figure 3-11d**). In addition, although the total emissions increase with vehicle electrification using the current gird, vehicle electrification relocates emissions from mobile sources (tailpipes) to stationary sources (power plants), making it relatively easier and cheaper to implement treatment measures [126]. Government subsidy does not result in more GHG reduction at low battery range (less than 120 miles), because vehicles that benefit less from PHEVs due to travel patterns are encouraged by the subsidy to adopt PHEVs while emissions reduced from gasoline displacement are not sufficient to make up the additional emissions from battery manufacturing.

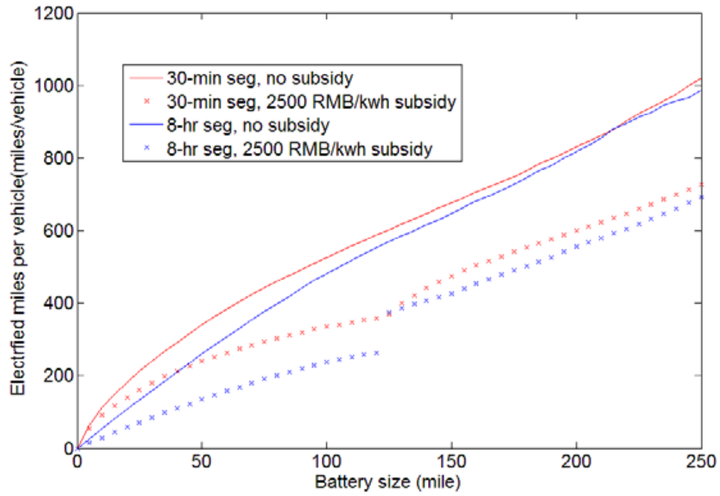

Figure 3-10. Electrified miles per vehicle regarding to battery sizes.

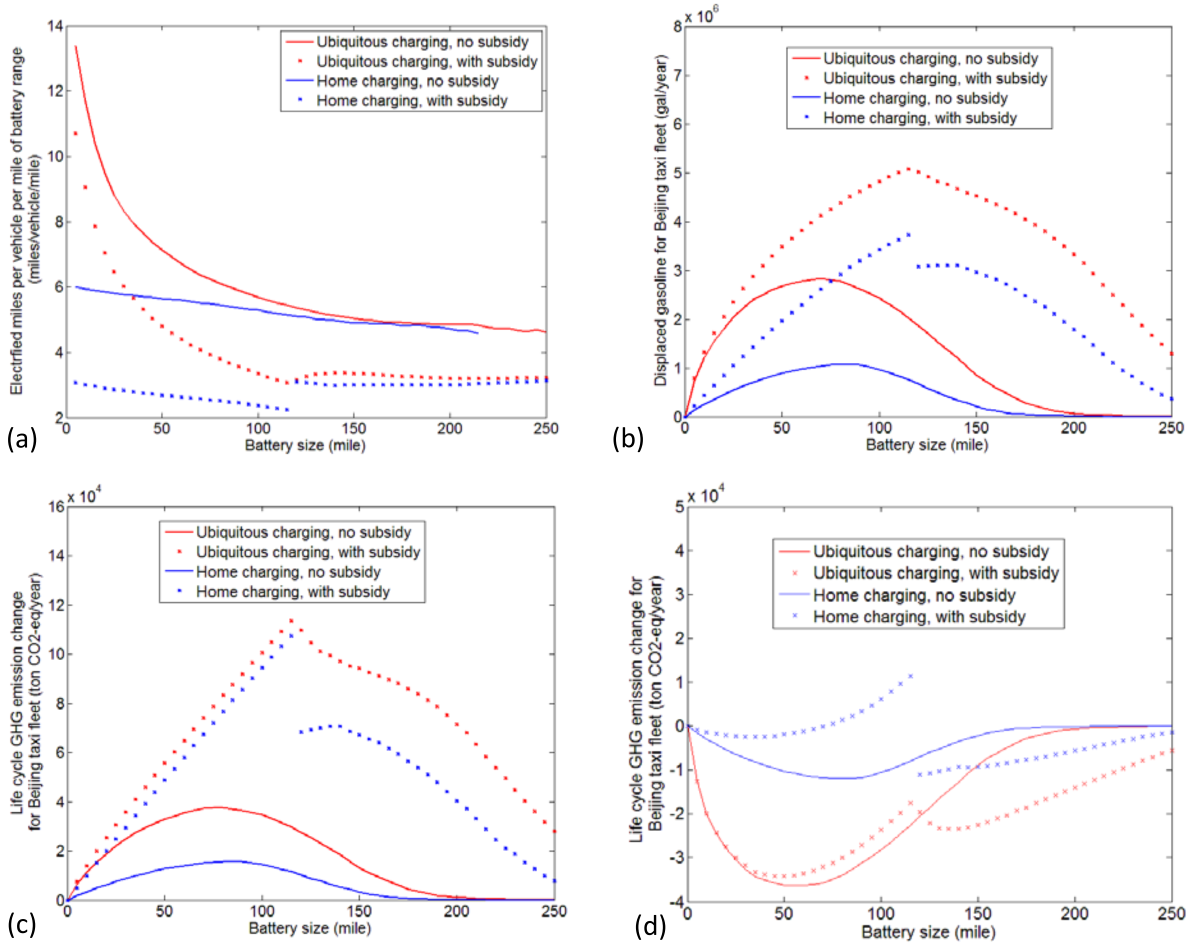

Figure 3-11. Marginal electrification rate, displaced gasoline and life cycle GHG emission change. Note: a) Marginal electrification rate (the amount of VMT electrified per vehicle due to one mile of additional battery range) and b) displaced gasoline with different PHEV battery size under different

charging and subsidy scenarios. Life cycle GHG emission change with different PHEV battery size under different charging and subsidy scenarios using fuel cycle emission factor of c) North China grid (which Beijing belongs to) and d) a cleaner grid scenario with 40% natural gas power plants and 10% efficiency improvement in coal-fired power plants. These scenarios are all modeled with battery cost at $500/kWh and subsidy at $401/kWh if applicable.

3.3.6 Policy Implications

At the current battery cost (approximately $400/kWh [130]), larger battery does not necessarily imply higher rate of adoption, utilization, and electrification of PHEVs due to the heterogeneous individual travel patterns. The VMT electrification rate peaks when PHEV battery range is around 90 miles, which represents the optimal battery size for the fleet at the current technologies.

While battery range is one of the major concerns from the consumers' perception [38], the results show that a larger battery can actually decrease the VMT electrification rate when unit battery cost exceeds $200/kWh. Only when unit battery cost is lower than $200/kWh, extended electric drive range can increase the adoption and thus electrification rate. In addition, the results show that charging opportunities (i.e., how frequently a driver can charge a vehicle) also play a key role in VMT electrification. Increasing charging speed only has marginal impacts, because when charging opportunities are limited (e.g., home charging only), each charging event has a relatively long duration, which allows most of the vehicles being fully charged even at the current charging speed.

Subsidy can effectively increase the VMT electrification rate by filling the gap between fuel cost savings and the premium cost of PHEVs. The results show that focusing on PHEVs with modest electric ranges (80 to 120 miles) can most efficiently boost taxi fleet VMT electrification with a fixed amount of budget. Iinstead of providing more subsidies for PHEVs with larger batteries, the government can design the subsidy program to target PHEVs with this medium battery range to achieve higher VMT electrification. The government can also consider an alternative program to subsidize electricity. Results from this study indicate that, with the same amount of total government spending, the same level of VMT electrification can be achieved by both types of subsidy programs. Different from a lump sum subsidy to incentivize PHEVs purchases, subsidizing electricity costs can further encourages PHEV owners to drive more on electricity. Currently most countries provide subsidies for EV purchases and only a few have additional subsidies for recharging electricity [127]. Because only adoption rates are currently reported as policy outcomes instead of VMT electrification rates, the contribution of subsidizing electricity for charging to current EV adoption and utilization is not clear and needs further exploration. In summary, this study demonstrates that better understanding of the individual travel patterns using large-scale trajectory data can help design better subsidy programs for PHEVs/BEVs adoption and utilization.

Last but not least, previous research on environmental impacts of PHEVs is often conducted based on average daily or annual VMT [131, 132]. This study demonstrates how individual travel patterns, charging opportunities, and battery size influence life cycle GHG emissions due to PHEVs adoption and utilization at the individual vehicle level. It also sheds light on the utilization of large-scale vehicle trajectory data for enhancing assessments of environmental impacts of PHEVs/BEVs.

3.3.7 Sensitivity Analysis

To assess the impacts of parameter variations on the results, I conducted a sensitivity analysis in reference to the baseline scenario. The baseline scenario has the following assumptions: home-charging only, no government subsidy, charging efficiency at 88%, electricity price at $0.078/kWh, gasoline price at $1.29/L, fuel economy for charging depletion mode at 0.35 kWh/mile, fuel economy for charging sustaining mode or conventional gasoline vehicle at 35 mile/gal, charging voltage at 240V, charging current at 16A, battery range at 80 miles, and battery unit cost at $500/kWh.

Results from the sensitivity analysis indicate that fuel cost reduction is more sensitive to charging opportunities than to charging speed (**Figure 3-12**). It is also more sensitive to gasoline cost and fuel economy than to electricity cost. In addition to these parameters, the electrification rate is also sensitive to acceptable payback time and the fuel economy in charge depletion mode **Figure 3-13**). I also tested the impact of the holiday on the electrification rate by separating the data into two subsets: before-holiday data and holiday data and compared the results obtained by using the entire dataset with those using the subsets. Results show that all three datasets lead to results with similar patterns (**Figure 3-14** and **Figure 3-15**). On holidays, the fleet has higher electrification rate because taxis drive less during the holiday and have more time to charge. In addition, electrification rates based on the entire week's data are generally lower than those based on the subset data, especially at larger battery range. This is due to the fact that segments crossing February 5th and 6th are cut into two shorter segments when data are separated into two subsets, which inflates the overall electrification rates.

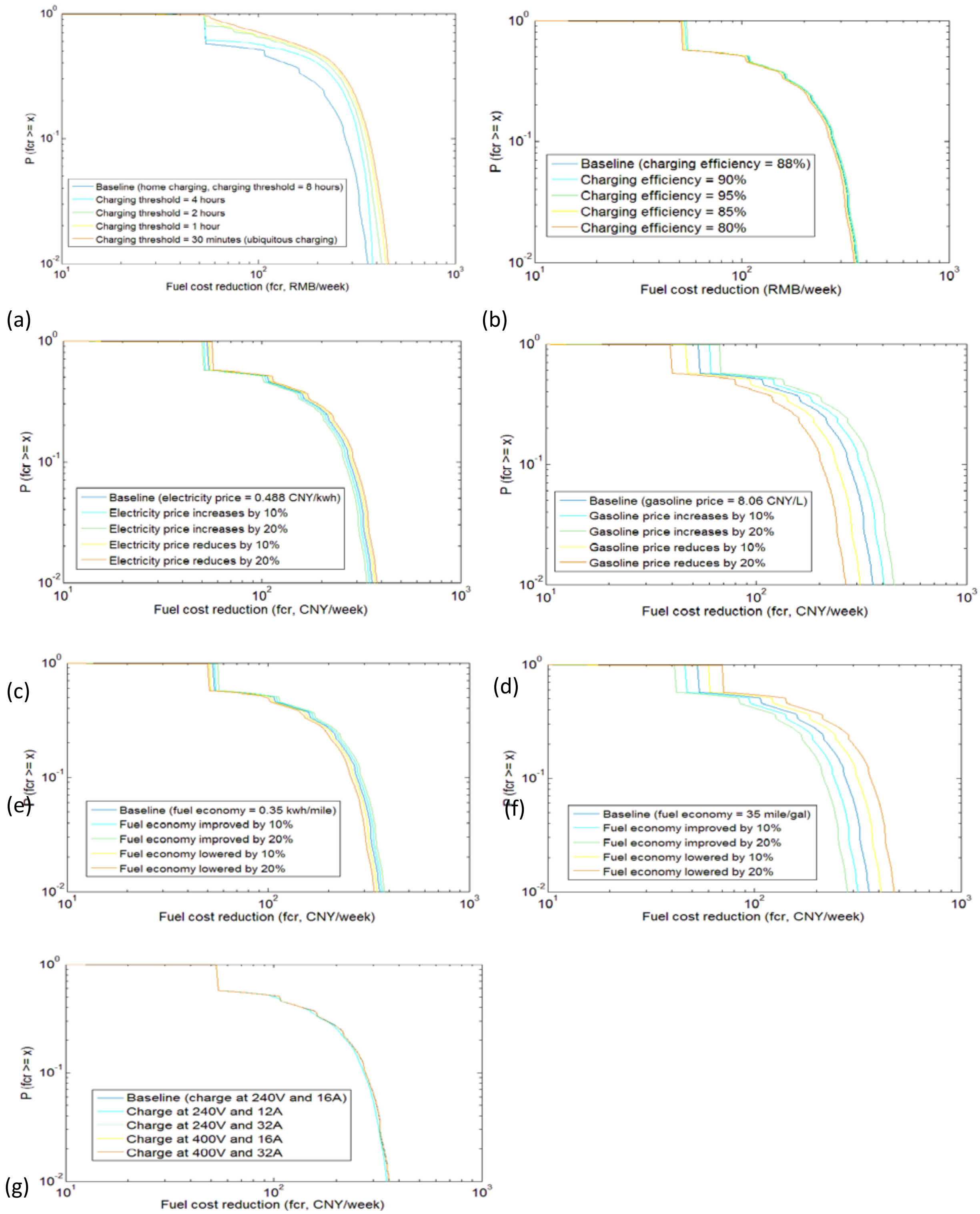

Figure 3-12. The sensitivity of fuel cost reduction to different model parameters.
Note: a) charging opportunities, b) charging efficiency, c) electricity price, d) gasoline price, e) fuel economy for charge depletion mode, f) fuel economy for charge sustaining mode, g) charging voltage and current.

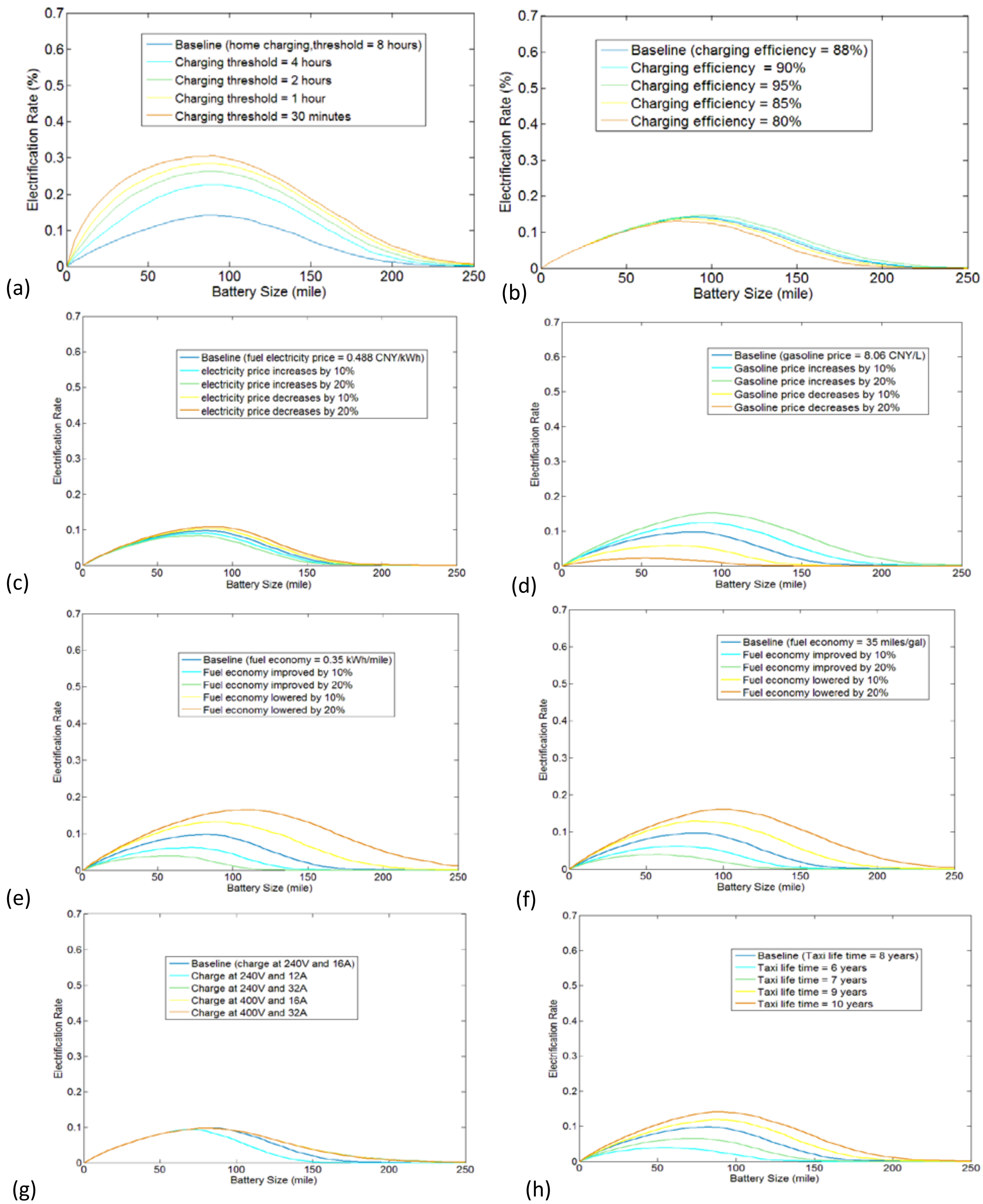

Figure 3-13. The sensitivity of electrification rate to different model parameters.

Note: a) charging opportunities, b) charging efficiency, c) electricity price, d) gasoline price, e) fuel economy for charge depletion mode, f) fuel economy for charge sustaining mode, g) charging voltage and current, h) acceptable payback time.

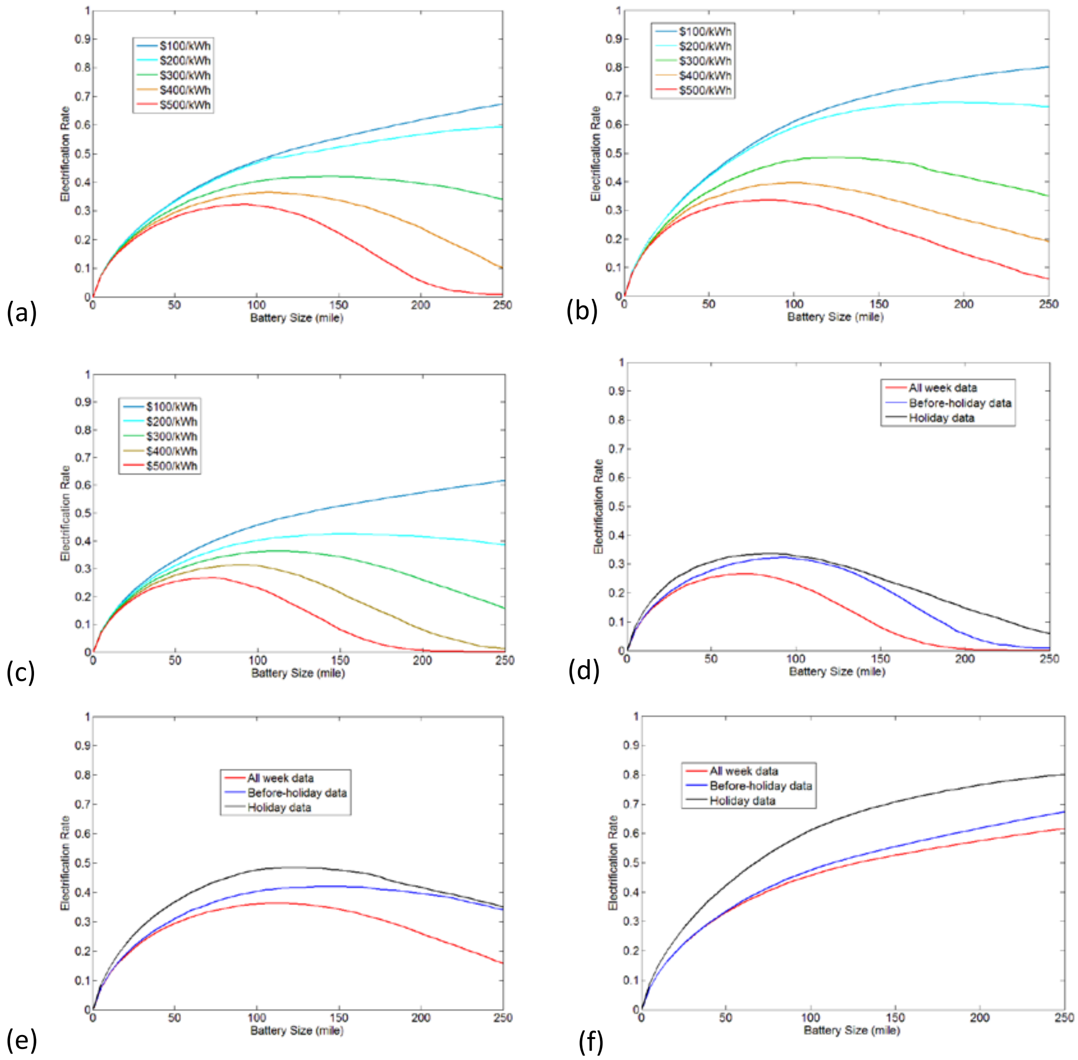

Figure 3-14. Impacts of the holiday on the electrification rate (ubiquitous charging).
Note: a) with subset of data before the holiday, b) with holiday data, c) with the full dataset, d) comparisons at $500/kWh battery cost, e) comparisons at $300/kWh unit battery cost, f) comparisons at $100/kWh unit battery cost.

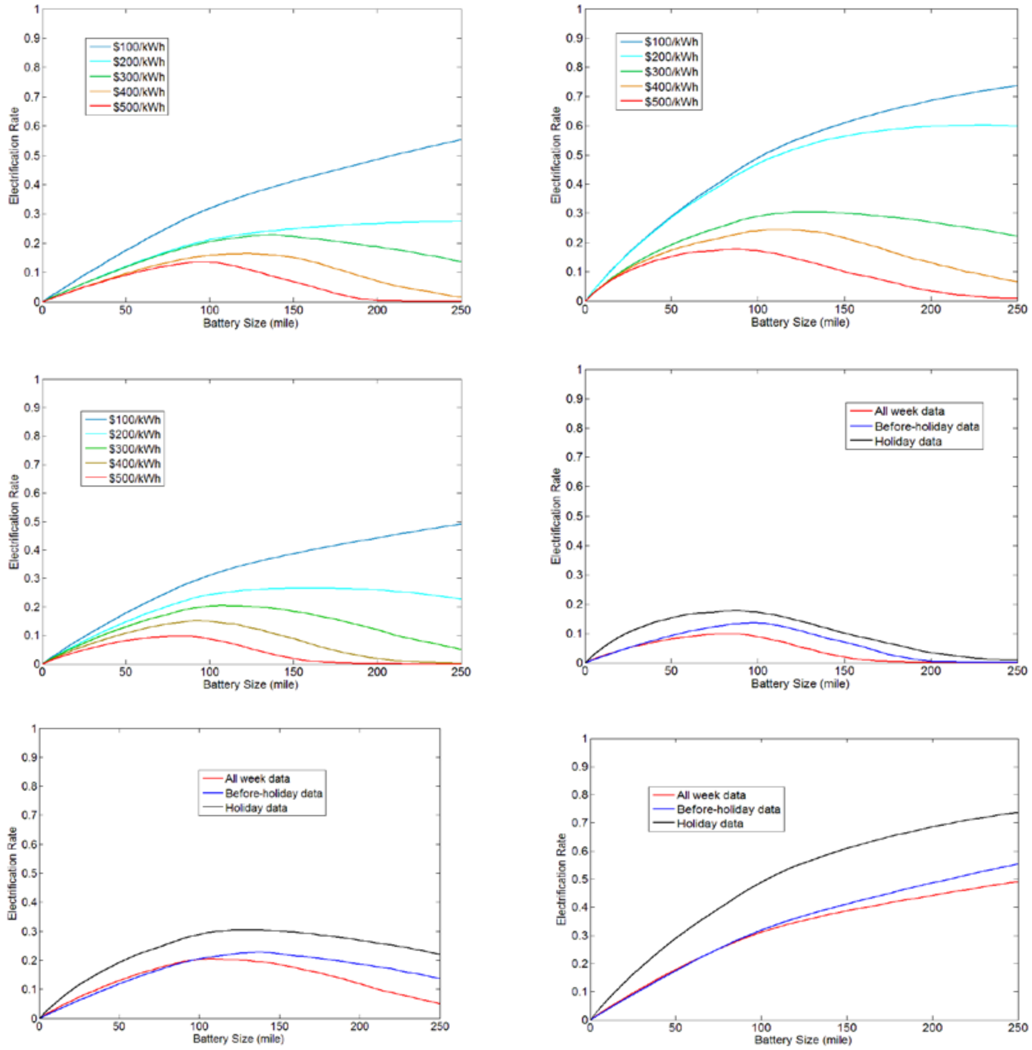

Figure 3-15. Impacts of the holiday on the electrification rate (home charging).
Note: a) with subset of data before the holiday, b) with holiday data, c) with the full dataset, d) comparisons at $500/kWh battery cost, e) comparisons at $300/kWh unit battery cost, f) comparisons at $100/kWh unit battery cost.

3.3.8 Study Limitations

While the data used in this study have the merit of including a large number of vehicles, the time span of available data for each vehicle is limited to a week including a national holiday. Because taxi usage is reduced during the holidays, the present dataset including taxi trajectories for the holiday may cause overestimation of the electrification rate. Given that weather conditions can also potentially impact the usage of taxis (e.g., more people may take taxis when it is raining), data with larger temporal coverage for a more representative period of time can improve this study. Nevertheless, the analytical framework developed in this study and key findings are still valid and valuable. This research also demonstrates the benefits of using individual travel patterns to study environmental implications of fleet electrification.

Another limitation of this study is that I assumed the adoption criteria are the same (i.e., payback battery cost within eight years) for everyone, and the entire fleet will choose PHEVs with the same battery size. While similar assumptions have been made in previous studies (e.g., [37]), the heterogeneity of tolerance level and diversity of consumer choices are lost. Although the taxi fleet is likely to use identical vehicles, individual drivers can have different adoption criteria regarding to payback time depending on their own risk tolerance levels and economic preferences. A survey of drivers' preferences can be supplementary to improve this study. Other factors impacting consumer choices (e.g., age of the current vehicle, drivers' economic conditions) are not considered in this study either. But this study can provide important guidance on developing realistic agent-based models (ABMs) with more sophisticated design of agents (i.e., consumers) that have heterogeneous adoption criteria and vehicle choices. Current ABMs (e.g. [103-105]) have not included the heterogeneity of individual travel patterns.

In addition to the serial powertrain configuration considered in this study, the power-split configuration can also be used for PHEVs, especially for vehicles with smaller batteries. Because the power-split configuration uses a combination of electricity and gasoline to power the vehicle, the overall electrification rates will be lower than using the serial configuration.

Furthermore, this study models SOC change as a linear process between 0% and 100% during charging and discharging. This simplification can lead to overestimation of electrification rates because the operating range of SOC is normally less than 100% for battery protection and the change of SOC becomes nonlinear when the battery is nearly depleted or almost fully changed [133]. More sophisticated battery charging and discharging simulation can improve this study with more accurate SOC estimations.

Lastly, temporal changes of emission factors, fuel economies, energy prices, and VMT are not accounted for in this study. These parameters are modeled as constants through the eight-year life time of taxis. While changes are expected with the rapid development of China, projections of these parameters over time bear high uncertainties and are thus out of the scope of this study. For the purpose of this study, perhaps it is better to evaluate the impacts of fleet electrification in isolation of these uncertain parameters.

3.3.9 Contribution of Individual Travel Pattern Data

Aggregated travel data can overestimate travel electrification by neglecting the variations of trip distances (and the existence of long trips) and assuming universal adoption of EVs. However, they can also underestimate travel electrification due to the lack of mid-day charging. Individual travel pattern data enable more flexible charging behavior and adoption modeling, and can better estimate the level of travel electrification that can be reached. Using average daily trip distance of 39 miles, Stephan and Sullivan (2007) assumed that PHEVs with 40 miles range can electrify 100% of the travel [22]. Based on aggregated travel distance distribution curve from travel survey data, Samaras and Meisterling (2007) calculated the utility factors for PHEVs with 30, 60, and 90 miles to be 47%, 68%, and 76%, respectively [25]. Using more detailed trip chain information from NHTS, Kelly et al. (2012) concluded that the utility factors can range from 63% to 76% for PHEVs with 42 miles and from 68% to 80% for PHEVs with 80 miles under different charging scenarios [34]. In this study, the electrification rates are much lower, at 22% to 28% for

PHEVs with 40-mile battery. These studies examine different fleets and have different model parameters and therefore cannot be directly compared. However, the lower rates of this research are mainly a result of the consideration of individual travel patterns and the usage of adoption model which allows the drivers whose travel patterns do not favor EV adoption to stay as ICE vehicles. In addition, this study shows that larger battery size may even reduce electrification rate compared to smaller ones. This mechanism cannot be captured if aggregated travel pattern data are used. Although results in Kelly et al. (2012) showed that improvement of utility factors using large battery size is constrained, the trend is still monotonously increasing or flattening out.

If aggregated travel pattern data are used for this study, for example, knowing the average daily VMT is 50 miles, the relationship between electrification rate and battery range is then linear as sketched in **Figure 3-12**. The electrification rate increases linearly with PHEV battery size until the battery size reaches 50 miles where the entire day's VMT can be electrified. The electrification rate stays at 100% when the battery size is over 50 miles and then suddenly dropped to zero when the large battery becomes too expansive to be paid back. Using aggregated data also limits the ability to analyze mid-day charging and has to assume that charging happens once per day at night after each day's travel. By providing the details of each driving and parking event, individual travel pattern data better support charging behavior modeling and better capture the system dynamics.

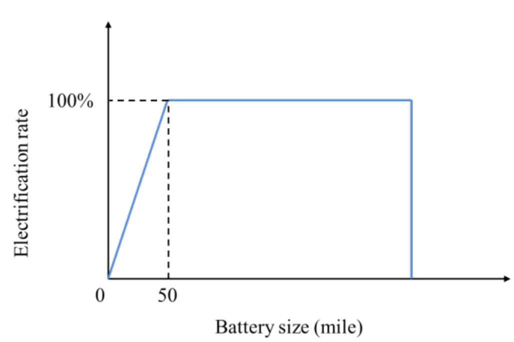

Figure 3-16. Relationship of electrification rate and battery size if aggregated travel pattern (average daily VMT at 50 mile is used).

3.4 Summary

Examining real-time vehicle trajectory data for 10,375 taxis in Beijing in one week, this study evaluates the impacts of adopting PHEVs in the taxi fleet on life cycle greenhouse gas emissions, considering the influences of individual travel patterns on PHEV adoption and utilization. The results indicate that 1) the largest gasoline displacement (1.1 million gallons per year) can be achieved by adopting PHEVs with modest electric range (approximately 90 miles) with current battery cost, limited public charging infrastructure, and no government subsidy; 2) reducing battery cost has the largest impact on increasing the electrification rate and gasoline displacement, followed by diversified charging opportunities; 3) government subsidies can be more effective to increase the VMT electrification rate and gasoline displacement if targeted to the PHEVs with modest electric ranges (80 to 120 miles); and 4) while taxi fleet electrification can increase greenhouse gas emissions by up to 115 kiloton CO_2-eq per year with current grid in Beijing, emission reduction of up to 36.5 kiloton CO_2-eq per year can be achieved if the fuel cycle emission factor of electricity can be reduced to 168.7 g/km. Although the results are based on a specific public fleet, this study demonstrates the benefit of using large-scale individual-based trajectory data to better understand environmental implications of fleet electrification and inform decision making.

CHAPTER IV

Public Charging Infrastructure Siting Informed by Individual Travel Patterns

4.1 Introduction

Charging infrastructure is critical to the development of the EV system [38]. Low availability of charging infrastructure can hinder EV adoption, which in turn reduces incentives to invest in charging infrastructure development [134]. Although charging stations have been increasingly installed in many cities, limited research has been done to study where charging stations should be built to maximize overall travel electrification. Mismatch of charging demand and charging infrastructure siting can lead to under-utilized charging infrastructure [135]. In Chapter III, two extreme charging scenarios are assumed: ubiquitous charging and home charging. Additionally, those assumptions consider only the vehicle resting time available for charging, but not the spatial distribution of charging demands and charging infrastructure. Realistically, a vehicle can only use the resting time to charge when it rests near a charging station. How will the spatial distribution of charging stations impact the electrification rate? Additionally, can individual travel patterns be used to better plan for siting charging stations? This chapter aims to answer these questions.

Estimating charging demand, especially public charging demand, is a difficult task due to the lack of realistic travel pattern data [136]. Previous studies use road traffic density [41], distribution of gas stations [42], and vehicle ownership [43-45] as proxies for charging demand.

Unlike gasoline or hydrogen fueling which only takes a few minutes, electric charging process is normally much longer and can take up to hours. As a result, charging is more likely to happen at the end of a trip rather than in the middle of a trip [46, 137]. Furthermore, in addition to charging vehicles at public charging stations, EV owners may have the option to charge at home. Therefore, traffic flow volume or vehicle ownership density does not necessarily represent the demand for public charging infrastructure. Realizing the importance of charging opportunity at the trip destinations, trips simulated with origin-destination pairs are also used to study charging demand [138-141]. Household travel surveys can provide detailed trip and parking information for surveyed individuals [137], but each individual is only surveyed for a limited duration (e.g., a day or two) with limited representativeness.

Recent attempts to use real world travel data to study charging infrastructure planning is constrained by the limited sample size of private vehicles [46]. Due to sampling cost and privacy concerns, sample size of private vehicles is usually in the hundreds. Because public charging demand is an emergent property of heterogeneous individual travel patterns, it is hard to draw conclusions at the fleet or city level using samples the size of which is several magnitudes lower than the fleet population. Fortunately, large-scale travel trajectory data of public fleets increasingly become available by the recent development of ICT. This affords unprecedented opportunities to better understand how charging infrastructures can be better planned to match real world charging needs. Although results concluded based on the public fleet data may not be directly applicable to private vehicles, methods developed for public fleets can be directly applied to private vehicles with similar travel trajectory data.

Another research gap for charging infrastructure siting is that, although different mathematical models are proposed [45-47, 138, 140], few studies consider potential environmental benefits of EV charging as the objective function. The ultimate goal of EV system deployment is to fulfill more travel needs using electricity instead of fossil-based liquid fuels. Higher fleet level travel electrification indicates higher potential environmental benefits from an EV system (assuming a low carbon grid). Therefore, given the transportation infrastructure's path dependence nature, it is also important to develop the charging infrastructure in a way that it can best realize the potential environmental benefits.

I aim to address both research gaps in this study by 1) using large-scale real world vehicle trajectory data to better model charging demand, 2) demonstrating that travel-pattern-informed charging stations can provide higher level of travel electrification, and 3) developing an optimization model to identify optimal charging station locations that can maximize fleet level electrifiedVMT. Using Beijing as a case study, this research examines a large-scale dataset containing travel trajectories of 11,880 taxis in Beijing for a month to study the impact of travel patterns on public charging needs and develops an optimization model that sites public charging stations to maximize potential environmental benefits. Public fleets (i.e., taxis and buses) are likely early adopters of EVs [98]. Beijing aims to put 100,000 EVs on roads by 2015 and build 466 charging stations to support these vehicles [142]. Results of this research can provide policy guidance for early stage charging infrastructure development in Beijing. In addition, this study demonstrates the benefit of using large-scale individual-based trajectory data to inform charging infrastructure development. Although this study only includes data from one type of fleet in a specific city, the framework and model developed are readily applicable to other fleets in other cities with similar data.

4.2 Data and Methods

There are two major views pertaining to the integration of public charging infrastructure into a city, gas-station-based and parking-lot-based, both of which has its own merits and disadvantages. Gas-station-based charging stations fit the existing consumer habits of vehicle refueling and can help reduce “range anxiety”. In addition, in the long term, while EVs gradually replace ICE vehicles, the increasing charging service can balance the decreasing refueling service at the gas stations and maintain efficient utilization of public infrastructure [143]. However, it is unrealistic to expect drivers to wait at gas stations if charging takes hours.

Parking-lot-based charging stations are more ideal for slow charging because it makes charging an add-on activity of a trip (e.g., work, shopping) and does not require extra time. However, in order to charge at the parking-lot-based stations, EV drivers often have to pay for parking fees which can be more expensive than the fuel cost saving. Because taxis in Beijing do not normally park for an extensive amount of time during the day and drivers tend to avoid paying unnecessary parking fees, this research focuses on the gas-station-based public charging stations. This gas-station-based charging approach has also been adopted in previous studies (e.g., [42, 143]).

This study includes two major tasks: 1) assessment of travel-pattern-informed charging infrastructure development; and 2) optimization of public charging station locations. The first task aims to demonstrate that using collective travel patterns to guide infrastructure development can help improve system level travel electrification. It also evaluates the environmental and electricity grid load impacts due to public charging. The selection of the charging station locations in this task is based on a simple scoring mechanism and therefore is suboptimal. The optimal solution also needs to consider the path dependence of vehicle SOC (whether the vehicle is charged at the previous resting event will determine the charging demand at the current resting location). The goal of the second task is to develop and solve an optimization model to identify charging station locations that can maximize system level travel electrification. The same vehicle trajectory dataset and model parameters are used in both tasks. The details of each task, data, and model parameters are explained in the subsections below.

4.2.1 Assessment of Travel Pattern-Informed Charging Station Siting

As shown in **Figure 4-1**, the first step is to extract taxi stop events from the trajectory data to evaluate public charging opportunities. Collective charging opportunity exists in locations where many taxis choose to stop for long durations. I then score each existing gas station based on how well it aligns with identified charging opportunity. A non-overlapping set of existing gas stations are then selected based on different criteria (e.g., maximal number of parking events, maximal daily parking time, or maximal average parking time per vehicle) as charging stations. It is worth noting that the identified charging opportunity is not the same as the charging demand. True charging demand depends on not only the parking time and location, but also the state-of-charge (SOC, representing the remaining capacity of the battery relative to the all-electric range) of the battery at the beginning of the parking event. A vehicle can park at a location for a long time but has low charging demand if its SOC is almost one (full battery) when it arrives at that location. To capture the true charging demand, I use trip chains extracted from the trajectory data and the selected charging stations to simulate PHEV adoption and charging. I assumed PHEV instead of BEV in this study for taxi electrification to allow drivers to finish trips that exceed the battery range on gasoline. The outputs of the mode are fleet level electrification rate, environmental impacts, and power load profile.

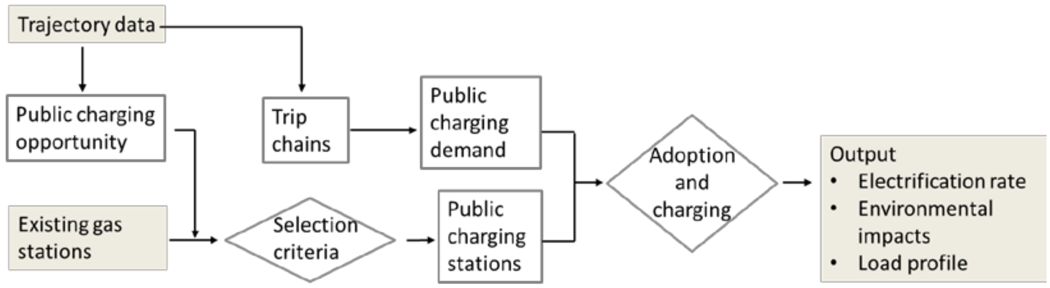

Figure 4-1. Model framework for Task 1

Similar to the adoption model described in **Section 3.2.5**, the adoption of PHEV is determined by the life time cost. Taxis will adopt PHEV if the life time cost of PHEV is cheaper than that of ICV. Adopted PHEVs will charge at home when they are parked at home (within 0.1 miles of identified home location). Because utility companies in Beijing currently offer to install free home charging outlets or posts for EV owners, I assumed that home charging is universally available without additional cost. The implications of this assumption on results are discussed in the Sensitivity Analysis (**Section 4.3.1.5**). When taxis are parked at non-home locations for more than 10 minutes, they will use the parking time to charge if there are public charging stations within 1 mile (1.6km) of the parked location. The service radius of 1 mile is used in this study to account for limited willingness of taxi drivers to change their behavior to accommodate for charging needs. This service radius is similar to the 2km range suggested by [42] but is less than the 5km range proposed by Beijing government [144]. Charging is assumed to start immediately after each vehicle is parked to fully utilize the resting time. The impact of this assumption is also evaluated in the Sensitivity Analysis (**Section 4.3.1.5**). Waiting in line for the charging port to become available or set up payment at the charging station can delay charging and reduce total charging time. I also assumed that the drivers are willing to charge their vehicle whenever they park near a charging station regardless of the current SOC of the vehicle. It is possible that the drivers only start to consider charging when the SOC is below a certain level. Therefore, the results in this study represent the upper bound of the fleet electrification rate. The detailed charging algorithm can be found in **Section 3.2.3**. Vehicle age is not considered in this study.

4.2.2 Optimization of Public Charging Station Locations

Let $G(i,j,k)$ be a network with i candidate locations for installing public charging stations, j individual PHEVs, and k trips for each vehicle during the examined period. The time spent between two consecutive trips is defined as the dwell time.

Each vehicle (j) has a remaining battery charge (R_{jk}) at the end of each trip (k) before starting its dwell time. For the convenience of modeling, R_{jk} is measured as the mileage that the vehicle can travel with the remaining electricity (battery range). R_{jk} can be formulated as shown in Eq. (1), with negative values of R_{jk} representing the mileage that cannot be powered by electricity (i.e., powered by liquid fuels) in trip k [46]. Eq. (2) shows the real remaining battery range ($\hat{R}_{jk}$) of vehicle j at the end of trip k, which is forced to be non-negative.

$$R_{jk} = \hat{R}_{jk-1} + E_{jk-1} - d_{jk} \quad \forall j \in J, \forall k \in K \tag{1}$$

$$\hat{R}_{jk-1} = max\{R_{jk-1}, 0\} \qquad \forall j \in J, \forall k \in K \tag{2}$$

where R_{jk} is the remaining battery range of vehicle j at the end of trip k (mile); E_{jk-1} is the electricity recharged (measured in miles) for vehicle j during the dwell time between trip k-1 and trip k; and d_{jk} is the travel distance (miles) of vehicle j during trip k.

Similar to the simulation in Task 1, this model also differentiates home charging and public charging. If vehicle j does not park at home after trip k ($h_{jk} = 0$), the vehicle seeks public charging opportunities. Electricity recharged for vehicle j after trip k (E_{jk}), as shown in Eq. (3), equals to the difference between the full battery range and the remaining battery range if the dwell time is longer than what is required to fully charge the battery, or the exact amount of electricity that can be charged if a full charge cannot be achieved within the dwell time. E_{jk} equals to 0 if no charging station is available for vehicle *j* at the end of trip *k*. If vehicle *j* parks at home after trip *k* (h_{jk} = 1), home charging is utilized. Recharged electricity at home, as shown in Eq. (4), equals to the difference between the full battery range and the remaining battery charge if the home parking time is longer than what is required to fully charge the battery, or the exact amount of electricity that can be charged during home dwell time.

$$E_{jk} = \min\left\{E_j - \hat{R}_{jk}, \frac{Le\, t_{jk}}{r_j}, M \sum_{i \in I} P_{ijk}\right\} \qquad if\ h_{jk} = 0 \tag{3}$$

$$E_{jk} = \min\left\{E_j - \hat{R}_{jk}, \frac{Lh\, t_{jk}}{r_j}\right\} \qquad if\ h_{jk} = 1 \tag{4}$$

where h_{jk} equals to 1 if vehicle *j* is parked at home after trip *k* and 0 otherwise; E_j is the effective all-electric range (AER) of vehicle *j*'s battery (measured in miles); *Le* is the charging power level (kW) at each of the public charging stations (assuming same for all public charging stations); *Lh* is home charging power level; t_{jk} is dwell time of vehicle *j* at the end of trip *k* (hour); r_j is the average electricity consumption rate of vehicle *j* in charge depletion (CD) mode (kWh/mile); *M* is a large number greater than E_j; and P_{ijk} is the availability of charging station for vehicle *j* at location *i* after trip *k*. P_{ijk} equals to 1 if candidate location *i* is accessible for vehicle *j* at the end of trip *k* and a charging station is installed at location *i*. Accessibility of charging station at location *i* by vehicle *j* is measured by the distance between location *i* and vehicle *j* at the end of trip *k*. If this distance is less than the service range of charging stations, location *i* is accessible.

The optimal selection of charging station locations in an area using the travel patterns of individual vehicles defined in this task is given by Eqs. (5) - (14). The objective function, as shown in Eq. (5), minimizes the total travel distances that cannot be fulfilled by electricity. This is equivalent as maximizing the electrified fleet VMT. Eqs. (6) to (8) formulate the remaining battery range of vehicle j at the end of trip k. In Eq. (7), R_j is the remaining battery range of vehicle j at the beginning of trip 1. Recharged electricity of vehicle j at the end of trip k is shown in Eqs. (9) and (10). Eq. (11) shows the budget constraint, limiting the maximum number of public charging stations as B. Charging opportunity is available at candidate location i for vehicle j at the end of trip k if two conditions are satisfied simultaneously, as shown in Eq. (12). The first condition requires the distance between candidate location i and the location of vehicle j at the end of trip k is less than the specified charging station service range. If vehicle j at the end of trip k is within the service range of candidate location i, Z_{ijk} equals to 1, otherwise zero. The second condition is that a charging station is installed at location i (y_i = 1). The model solves y_i for the optimal solutions. Eqs. (13) and (14) show the binary and positive variables, respectively.

$$\min \sum_{k\in K}\sum_{j\in J}\left(\hat{R}_{jk} - R_{jk}\right) \tag{5}$$

Subject to:

$$R_{jk} = \hat{R}_{jk-1} + E_{jk-1} - d_{jk} \qquad \forall j \in J, \forall k \in K \tag{6}$$

$$R_{j1} = R_j - d_{j1} \qquad \forall j \in J \tag{7}$$

$$\hat{R}_{jk} = max\{R_{jk}, 0\} \qquad \forall j \in J, \forall k \in K \tag{8}$$

$$E_{jk} = \min\left\{E_j - \hat{R}_{jk}, \frac{Le\ t_{jk}}{r_j}, M\sum_{i\in I} P_{ijk}\right\} \quad if\ h_{jk} = 0,\ \forall j \in J, \forall k \in K \tag{9}$$

$$E_{jk} = \min\left\{E_j - \hat{R}_{jk}, \frac{Lh\ t_{jk}}{r_j}\right\} \qquad if\ h_{jk} = 1,\ \forall j \in J, \forall k \in K \tag{10}$$

$$\sum_{i\in I} y_i \le B \tag{11}$$

$$P_{ijk} = Z_{ijk}\, y_i \qquad \forall j \in J, \forall k \in K, \forall i \in I \tag{12}$$

$$P_{ijk}, y_i \in \{0,1\} \qquad \forall j \in J, \forall k \in K, \forall i \in I \tag{13}$$

$$\hat{R}_{jk}, E_{jk} \ge 0 \qquad \forall j \in J, \forall k \in K \tag{14}$$

where the decision variables of the problem are as follows:

R_{jk}: The remaining battery range of vehicle j at the end of trip k (mile)

$\hat{R}_{jk}$: The real remaining battery range of vehicle j at the end of trip k (mile)

P_{ijk}: Binary variable which shows the availability of public charging for vehicle j at the end of trip k at location i, with 1 indicating available and otherwise 0

y_i: Binary variable which shows whether a charging station is installed at location i, with 1 indicating present and otherwise 0

E_{jk}: Battery electricity recharged for vehicle j at the end of trip k (mile)

Vehicle travel behavior varies from day to day. To capture this variation and examine model sensitivity, I separate the trajectory data into three weekly datasets and apply model to each. For each week, the data are prepared into four input matrixes, $D(d_{jk})$, $T(t_{jk})$, $H(h_{jk})$, and Z (Z_{ijk}), where d_{jk} is the travel distance of vehicle j during trip k (mile), t_{jk} is dwell time of vehicle j at the end of trip k and before trip $k+1$ (hour), h_{jk} is a 0-1 matrix with 1 indicating that vehicle j parks at home during its dwell time at the end of trip k and 0 indicating that it does not park at home during the dwell time, and Z_{ijk} is 1 if vehicle j is parked within the service range of candidate location i at the end of trip k, and zero otherwise. The same service range of 1 mile is used in this task as well.

The proposed optimization model is a Mixed Integer Problem (MIP). It is implemented in GAMS with Cplex solver. Although only gas-station-based charging stations are evaluated in this study, the same optimization model can be applied to candidate locations based on other criteria (e.g., parking-lot-based) as well with modified inputs reflecting the new candidate locations.

4.2.3 Data and Model Parameters

Data used in this study are vehicle trajectory data of Beijing taxis. Currently there are approximately 66,000 taxis in Beijing [101, 145]. Taxis generally do not work for a dispatch center. Instead, they mainly provide hail service, which means that the taxis cruise along the streets and look for clients who signal their needs for taxis. Drivers possess the vehicle 24/7 and normally park it where they live when they are off work. These properties make Beijing taxis share some characteristics with private vehicles (e.g., park at home at night and routine trips leaving and returning home). Although some taxis may have multiple shifts (two or more drivers drive the same vehicle in turns), the majority of the taxis only have one dedicated driver (single shift) [146]. Approximately 79.8% of the taxis analyzed in this study have an average dwell time of at least five hours per day.

After data curation, the dataset used in this study contains continuous trajectory data of 11,880 taxis (18% of the fleet) in Beijing over a period of three weeks (March 2 to 25, 2009). It includes a total of 255 million data points which covers 3.4×10^7 miles of travel and over 2 million trips. Each data point contains the timestamp up to seconds (when the data is recorded), vehicle ID, and vehicle location at the recorded time (in longitude and latitude). Home locations are identified as the location where taxis consistently park at night. Trip chains are extracted with a threshold of minimum parking for five minutes for Task 1 and a threshold of fifteen minutes for Task 2. The higher threshold set for Task 2 is with the consideration of reducing computation intensity for solving the optimization problem and reflecting more conserved charging behavior (I assumed that drivers are unlikely to go through the hassle of charging if they have too little time).

This study includes the following key parameters. Home charging has a voltage and current at 220V and 10A. Public fast charging has power output of 37.5kW [147], while public slow charging is at 220V and 32A [148]. Charging efficiency is 88% [34]. The all-electric range (AER) of the modeled PHEV is 100 miles. Unit battery cost is at $300/kWh. The electricity price is at $0.078/kWh while the gasoline price is at $4.86/gal. Life time of a taxi is eight years. It is assumed that no battery replacement is needed during the taxi's life time. Each vehicle's mileage varies depending on its travel pattern. The net present value (NPV) is calculated with a discount rate of 5%. Fuel cost escalation over time is not considered in this model. Fuel efficiency is 0.35kWh/mile during electric mode and 35 mile/gal during gasoline mode [120]. The current government subsidy for PHEV purchase is $11,240 per vehicle ($5,620 central government subsidy with an additional 1:1 match from the Beijing government) [149]. For environmental impacts, I used emission factors adopted from other studies focused on vehicle emissions in China. The emission factors are 236.7 g CO_2-eq/km [126], 0.0797g $PM_{2.5}$/km, 0.1336g PM_{10}/km, 11.457g SO_2/km, 0.5384g NO_x/km, and 0.138g CO/km [32] for distance driven in electricity; and 224.4 g CO_2-eq/km [126], 0.0045g $PM_{2.5}$/km, 0.012g PM_{10}/km, 0.135 SO_2/km, 0.42g NO_x/km, and 1.905g CO/km [32] for distances driven in gasoline. I use 0.47 kg CO_2/kWh for CO_2 emission from natural gas generated electricity [150].

4.3 Results and Discussion

4.3.1 Assessment Results (Task 1)

4.3.1.1 Public Charging Opportunity

The duration when a taxi is parked at non-home locations (e.g., for the driver to rest, have dinner, or wait for the next client) represents public charging opportunities for this taxi without requiring behavior change from the driver. Therefore, locations near which many taxis choose to park for an extensive amount of time can be candidates to build charging infrastructure. This overall charging opportunity can be quantified using “vehicle-hour”, where 1 vehicle-hour means the equivalent of one vehicle parks at a location for an hour (or equivalently two vehicles each park for half an hour). The probability density distribution of vehicle-hour shows that while most parking events happen in the city, regional “hotspots” exist for both suburbs (**Figure 4-2a**) and inner city (**Figure 4-2b**).

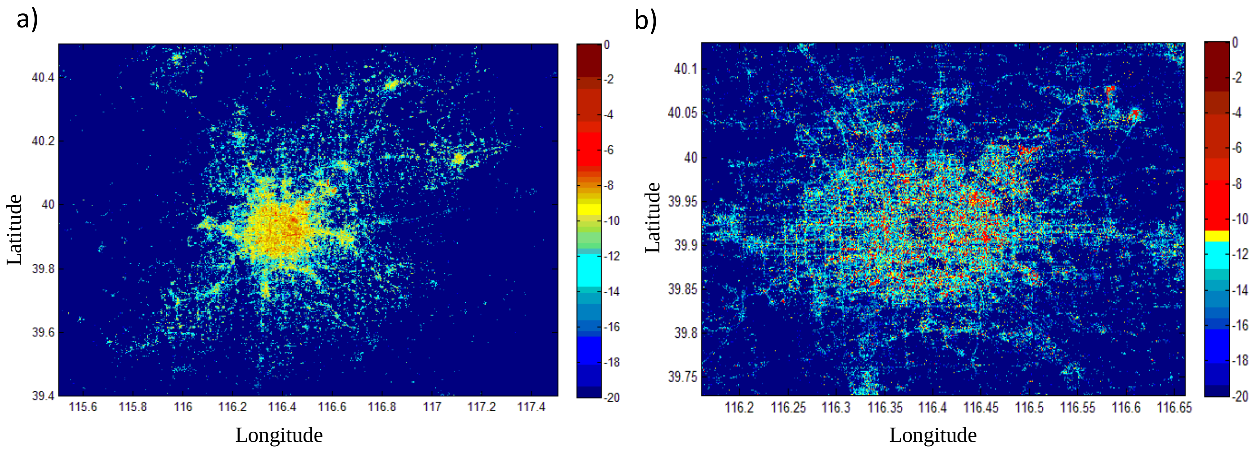

Figure 4-2. The probability density distribution of vehicle-(parking)-hour for taxis in Beijing. Note: a) shows the entire Beijing administrative region and b) shows zoomed inner city. Both figures are in log scale.

4.3.1.2 Evaluation of Gas-Station-Based Charging Stations

I use three criteria to select existing gas stations for their suitability to be expanded as charging stations: 1) the total number of parking events happened in the service range (1 mile) of the gas stations; 2) average vehicle-hour per day within the service range of each gas station; and 3) average vehicle-hour per vehicle within the service range of each gas station. Gas stations with the most parking events (**Figure 4-3a**) and daily vehicle-hours (**Figure 4-3b**) are concentrated in the center of the city while gas stations with the highest vehicle-hour per vehicle located in the suburb (**Figure 4-3c**). This difference shows that charging stations located in the center of the city can provide access to more taxis but may not provide long enough time to achieve full charge due to limited charging time. In contrast, charging stations located in the suburb may provide longer charging time but will only be able to serve a small number of taxis.

At the time of the study, Beijing had 40 charging stations/posts built (**Figure 4-3d**). I compared the overall mileage electrification rate of the taxi fleet provided by the 40 existing charging stations and 40 gas-station-based charging stations selected based on each of the three different criteria. The results show that gas-stations selected based on either the total number of parking events or vehicle-hours per day are more suitable for adding charging capability in order to achieve higher electrification rate (**Figure 4-4**). Well selected gas-station-based charging stations can improve the overall fleet level electrification rate by 37%. Home charging alone can electrify 24% of the mileage for the taxi fleet. This can be improved to 35% with existing 40 charging stations and 48% with the same number of gas-station-based charging stations selected using the total number of parking events with fast public charging. The increased electrification rate means that up to 46.4 million gallon of gasoline can be displaced per year by having 40 public charging stations. Average per vehicle parking time is not a good selection criterion when the density of the charging stations is still low. With slow public charging, the same trend exists but the overall electrification rates are reduced by 20% for existing charging stations and by 45% for gas-station-based charging stations selected with total number of charging events. The disproportional reduction shows that it is more critical to build fast charging stations at locations that match charging demand.

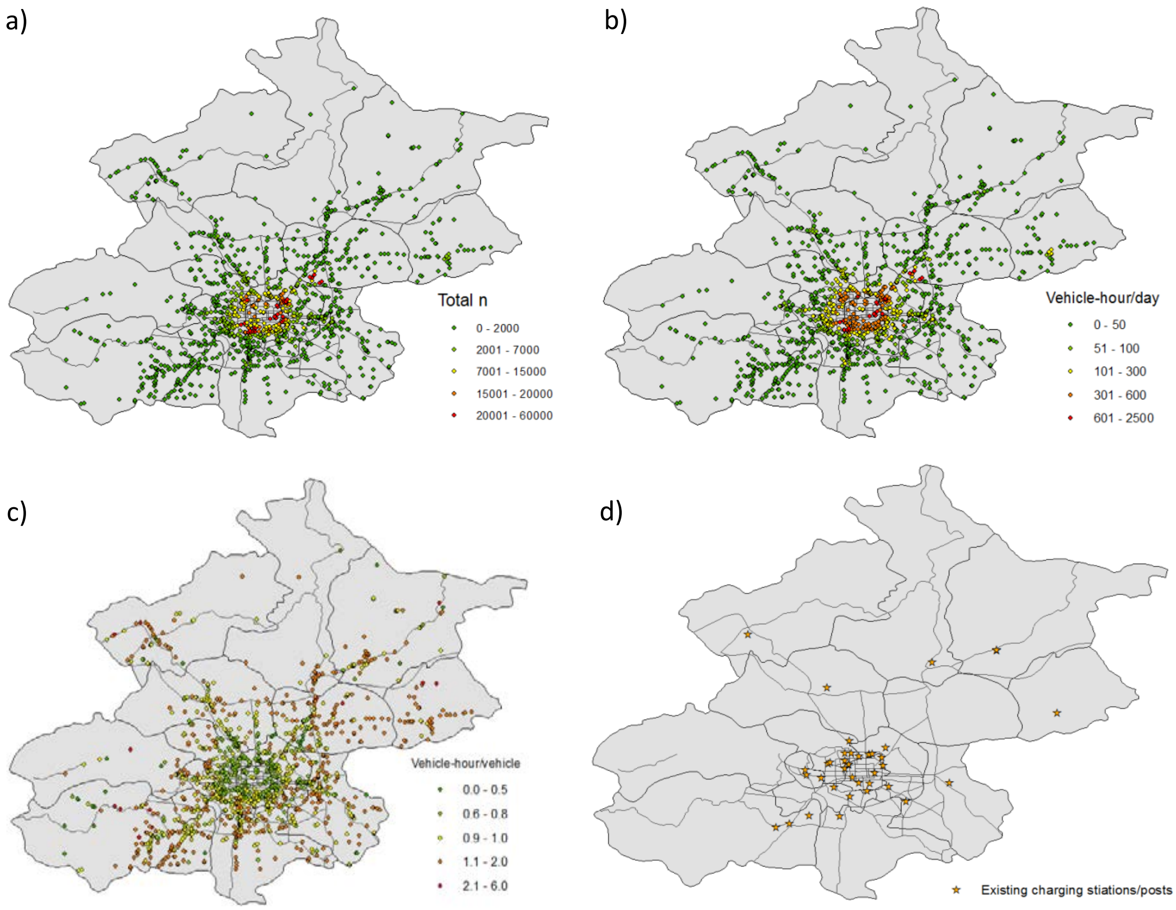

Figure 4-3. Locations of existing gas stations in Beijing.
Note: The stations are color-coded with a) total number of parking events within service range (1 mile) of the gas station; b) average daily vehicle-hour within service range; and c) parking time per vehicle. d) Location of currently existing charging stations and posts.

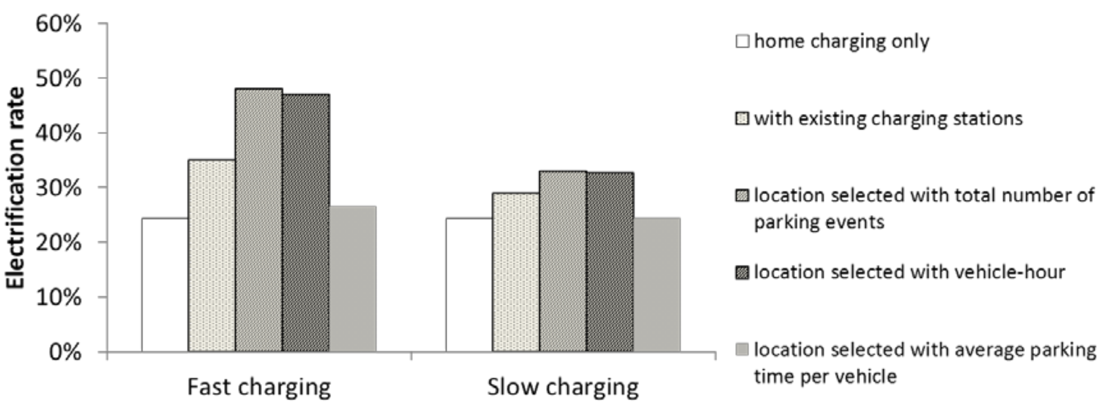

Figure 4-4. Overall mileage electrification rate of the taxi fleet with different charging scenarios.

4.3.1.3 Environmental Impacts

In addition of displacing gasoline, higher electrification rate of the taxi fleet will impact air emissions as well. Because electricity in the North Grid, where Beijing is located, is currently generated with 98% coal [126], CO_2, $PM_{2.5}$, PM_{10}, SO_2, and NO_x emissions will increase with higher electrification rate while CO emissions can be reduced (**Table 4-1**). Although the current grid mix makes EVs cause more emission than ICE vehicles in Beijing, it is promising to achieve emission reduction when the grid becomes cleaner [126]. For example, as discussed in Chapter III (**Section 3.3.5**), when the penetration of natural gas-fired electricity reaches more than 10.3%, CO_2 emissions can then be reduced. In addition, relocation of emissions from mobile sources (tailpipes) to concentrated sources (power plants) makes it easier to implement emission reduction and treatment mechanisms [151].

Table 4-1. Emission change under different charging scenarios.

	Emission changes (ton/year)	**CO_2**	**$PM_{2.5}$**	**PM_{10}**	**SO_2**	**NO_x**	**CO**
Fast charging	Home charging only	1,063	7	11	979	10	-153
	With existing charging stations	1,530	9	15	1,409	15	-220
	Location selected with total number of parking events	2,103	13	21	1,935	20	-302
	Location selected with total vehicle-hour	2,054	13	20	1,891	20	-295
	Location selected with average parking time per vehicle	1,161	7	11	1,069	11	-167
Slow charging	Home charging only	1,063	7	11	979	10	-153
	With existing charging stations	1,267	8	13	1,166	12	-182
	Location selected with total number of parking events	1,442	9	14	1,328	14	-207
	Location selected with total vehicle-hour	1,427	9	14	1,313	14	-205
	Location selected with average parking time per vehicle	1,064	7	11	980	10	-153

4.3.1.4 Power Grid Load Impact

Based on the scenario of 40 charging stations, the average power grid load impact from public charging is presented in **Figure 4-5**. The peak demand is around noon time which overlaps with the city's day time electricity demand peak [42]. Fast public charging results a more significant load shock comparing to slow public charging, which indicates that charging time management policies need to be implemented with the deployment of fast public charging stations.

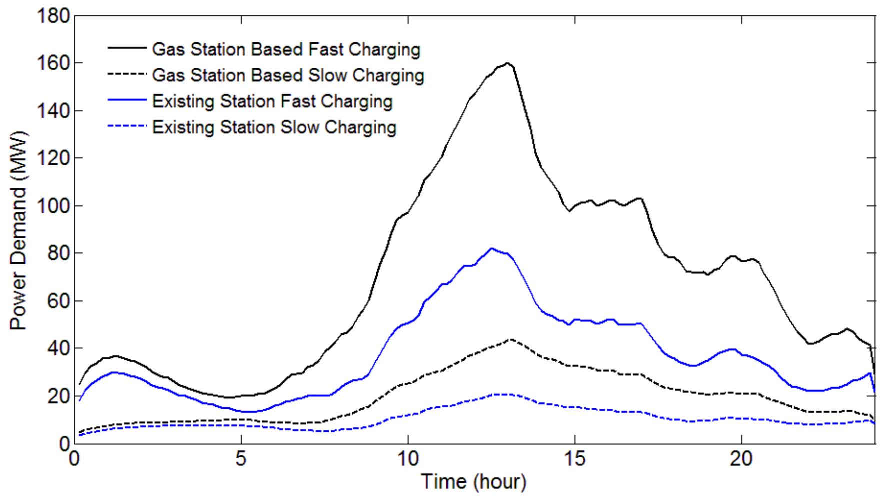

Figure 4-5. Electricity load profile with 40 public charge stations.

4.3.1.5 Sensitivity Analysis

Key assumptions and parameters made in this task include the availability of home charging, parking time, and battery range. This section discusses how these assumptions and parameters affect the results.

I assume that home charging is available for all taxis. Among all parking events during a day, home parking is usually the longest and represents important charging opportunities. While it is important to capture these charging opportunities at home, significant barriers (e.g., requirement of dedicated parking space and accessible residential outlets) still exist to reach universal accessibility [152, 153]. If home charging is not available, the overall electrification rate is reduced for all charging scenarios (**Figure 4-6**).

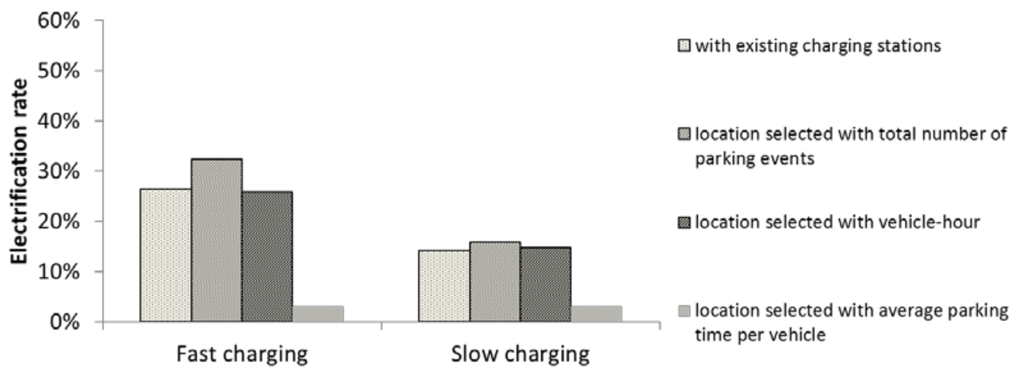

Figure 4-6. Overall mileage electrification rate of the taxi fleet with different charging scenarios when home charging is not available.

Parking time determines how much electricity taxis can charge at each station. When parking time is increased or decreased by 10%, electrification rate increases or decreases by 3-5% for the fast charging scenario (**Figure 4-7a**). Slow charging is slightly more sensitive to parking time: electrification rate increases or decreases by 5-6% in response to 10% parking time changes (**Figure 4-7b**). When single-shift taxis convert to double-shift ones, in addition to losing home charge opportunities and increased number of trips, parking time at each park event may also be reduced because drivers may rest less to take advantage of the fixed 12-hour shift time. In an extreme scenario that all taxis have multiple shifts, the overall electrification rate is lower than those shown in **Figure 4-6** for no-home-charging conditions.

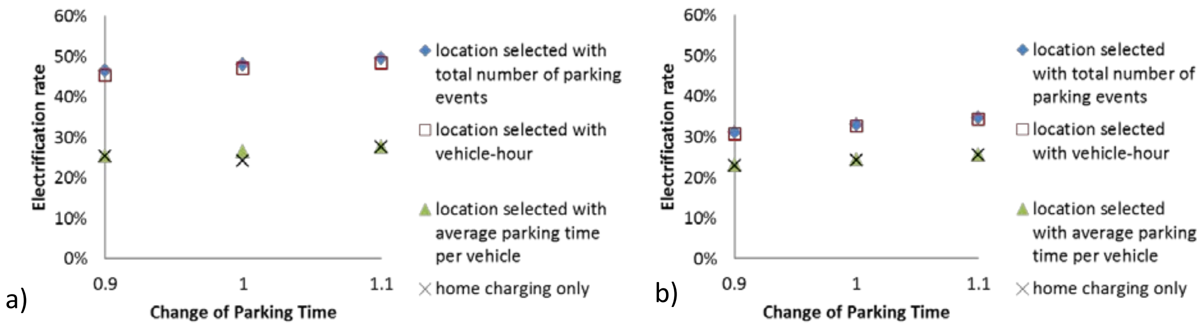

Figure 4-7. Sensitivity of electrification rate to the change of parking time.
Note: Baseline parking time is represented as "1". "1.1" means increase parking time at each parking event by 10% while "0.9" means decrease by 10%. a) Fast charging and b) Slow charging.

The relationship between electrification rate and battery range is an inversed "U" shaped curve (**Figure 4-8**), similar to what is observed in Chapter III. A battery with larger all-electric range can initially increase the overall electrification rate, which declines when increased battery cost causes adoption reduction. Electrification rate peaks earlier for slow charging than for fast charging, which means that the benefit of having larger batteries will be constrained by the charging speed.

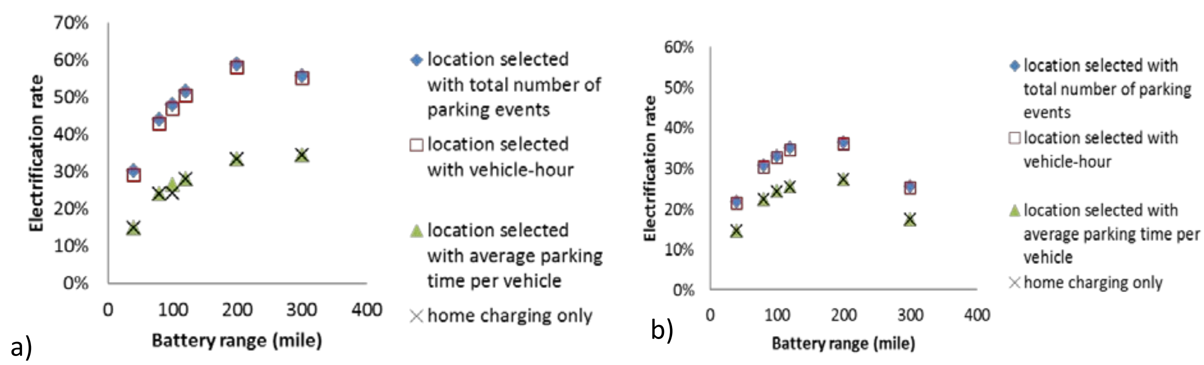

Figure 4-8. Sensitivity of electrification rate to the change of battery range.
Note: a) Fast charging and b) Slow charging

4.3.2 Optimization Results (Task 2)

<u>4.3.2.1 The 40-Station Scenario</u>

Similar to Task1, I compare the optimized results with those of the 40 existing charging stations. As shown in **Figure 4-9**, while existing charging stations can electrify 29±3% and 35±2% of the fleet VMT with slow charging and fast charging respectively, location-optimized stations can effectively increase electrified fleet VMT to 46±4% and 66±2%, on average an 59% and 88% improvement. Compared to the locations of the existing stations, the optimized stations are concentrated in the inner city regardless of the variations in the weekly data (**Figure 4-10a** to **c**). It is notable that, while the location of optimized stations in the suburban area varies from week to week, the selection of optimized stations in the inner city is quite consistent (**Figure 4-10d**). By zooming into the inner city, it is clear that the locations of the optimized stations are quite different from those existing ones (**Figure 4-11a** to **c**). The significant charging demand near the Beijing Capital International Airport is not currently covered by the existing stations (**Figure 4-11d**).

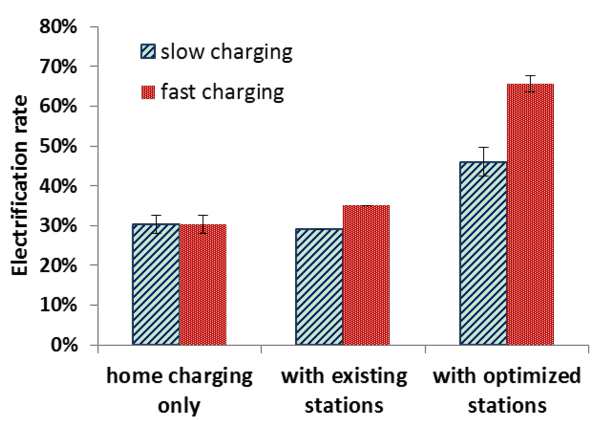

Figure 4-9. Electrified fleet VMT as percentage of total fleet VMT (electrification rate) for existing and optimal public charging stations

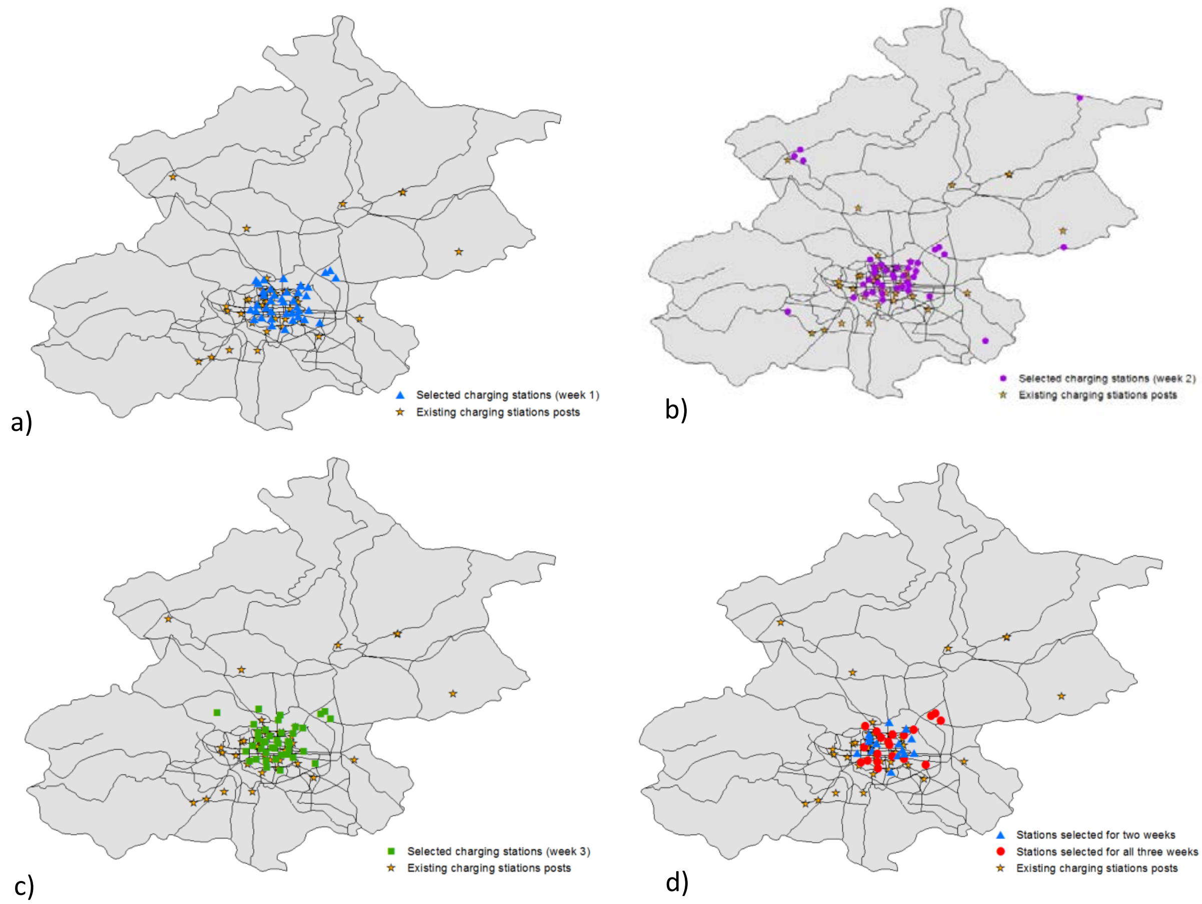

Figure 4-10. Locations of the optimized charging stations in the 40-station scenario.
Note: the locations are selected using a) data from week 1; b) data from week 2, and c) data from week 3. Charging stations selected as the optimal choices in two or three weeks are highlighted in d) with blue and red color, respectively.

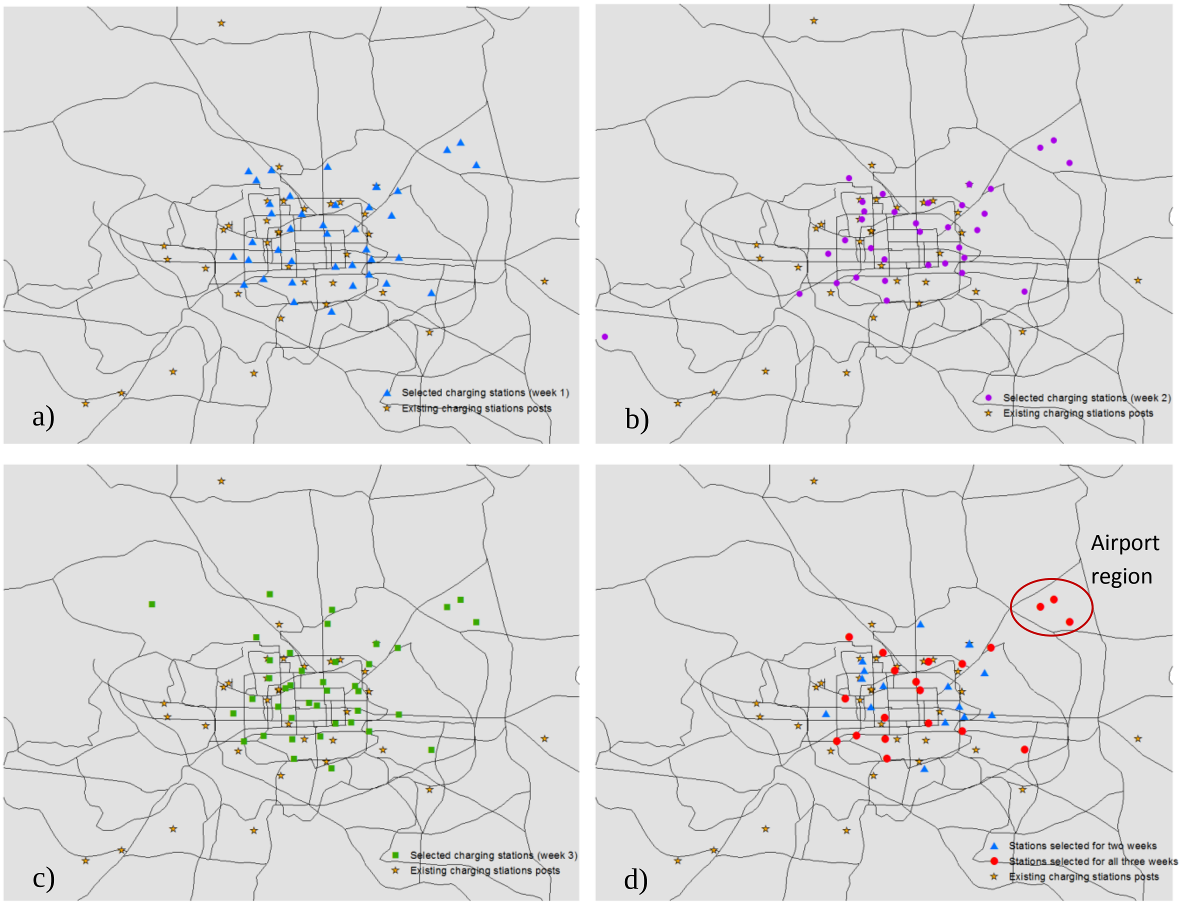

Figure 4-11. Location comparison of optimized stations and existing stations in the inner city of Beijing
Note: a) optimization results with data for week 1; b) optimization results with data for week 2; c) optimization results with data for week; and d) optimal locations selected in two or three weeks.

4.3.2.2 Impacts of Increased Number of Charging Stations

To evaluate the impact of the total number of stations that can be installed (*B*) on the optimization results, I ran models ranging *B* from 20 to 500. The results show that, while increasing the total number of charging stations increases electrified fleet VMT regardless of charging speed, the marginal electrified fleet VMT for both type of charging stations quickly diminishes (**Figure 4-12**). The difference in electrified fleet VMT between installing the same number of fast and slow charging stations diverges initially but stays stable at about 20% when there are 40 or more charging stations.

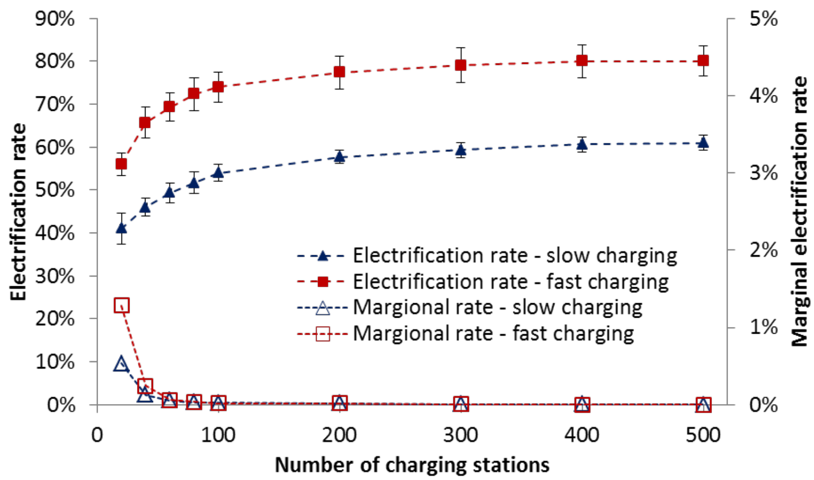

Figure 4-12. Change electrification rate and marginal electrification rate with increasing number of charging stations

Optimized stations concentrate in the inner city in all scenarios, gradually expanding to the suburban area with increasing number of charging stations (**Figure 4-13**). To measure how many of the selected stations remain the optimal choice when the total number of charging stations is increased, I define retention rate as the percentage of selected stations in a scenario with smaller number of stations remains as the optimal choices in a scenario with greater number of stations. For example, if half of the stations in the 40-station scenario are also selected as the optimal choices in the 60-station scenario, the retention rate is 50% (20 divided by 40). As shown in **Figure 4-14**, on average, the overall retention rate is 70% to 88% for slow charging and 67% to 88% for fast charging, which indicates that the majority of the optimal stations are consistently selected even when the total number of charging stations are increased by 25 times. In general, the optimal slow charging stations have higher retention rate than the fast charging ones, showing that slow charging stations selected for short term planning (i.e., scenarios with less total number of stations) are more likely to stay as the optimal choices for long term planning (i.e., scenarios with larger total number of stations). Additionally, the standard deviation of the retention rate reduces with increasing total number of charging stations, showing that the variation of travel pattern among different weeks can be better covered with more charging stations. With 200 charging stations, the standard deviation of retention rate can be effectively reduced to less than 3%.

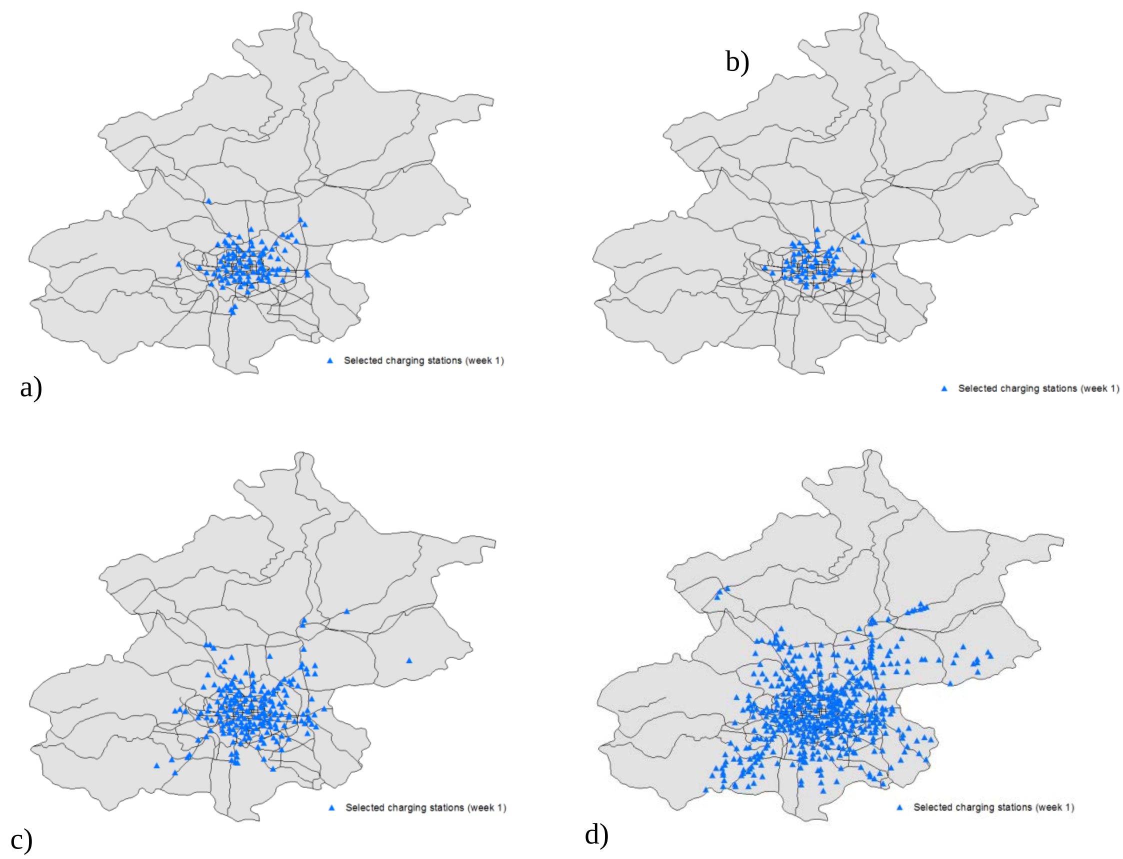

Figure 4-13. Locations of optimized stations in scenarios with different total number of charging stations.

Note: a) 60 stations, b) 100 stations, c) 200 stations, and d) 500 stations.

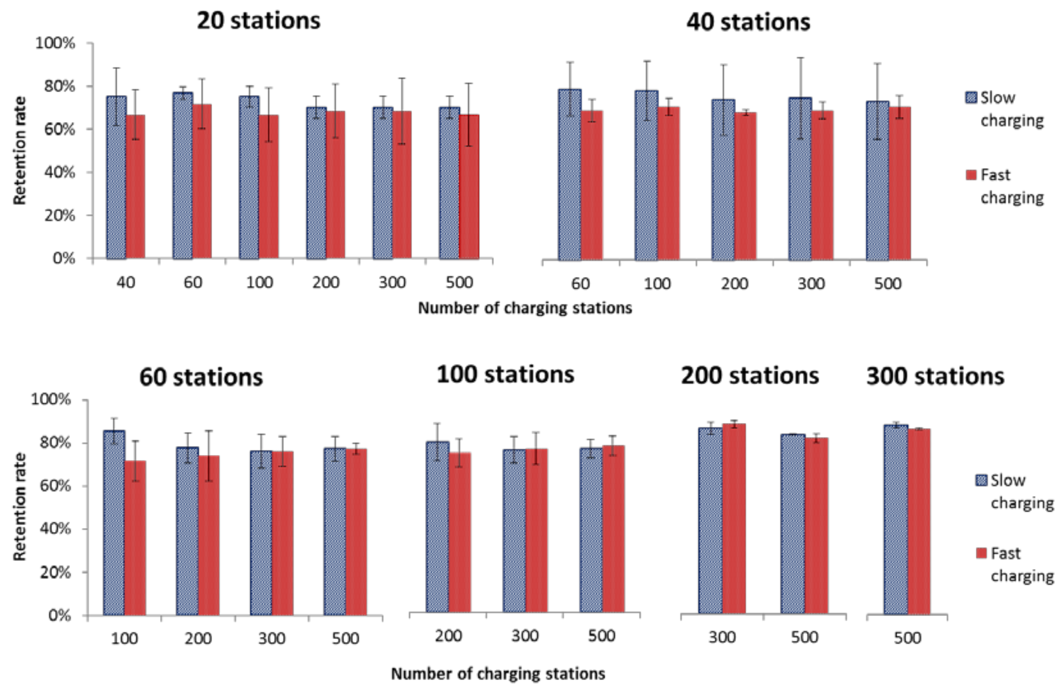

Figure 4-14. Retention rate of selected stations when increasing total number of charging stations

4.3.3 Limitations

This study demonstrates the benefits of using individual travel patterns derived from large-scale real-world vehicle trajectory data to inform public charging infrastructure development. It proposes a novel approach to estimate public charging demand and develops an optimization model to site public charging stations to maximize travel electrification. However, due to data availability and the assumptions made, this study has the following limitations.

First, this study assumes that data collected for the 11,880 taxis are representative for the entire taxi fleet which consists of approximately 66,000 taxis. Although I have not observed any specific bias in the data, the representativeness of the spatial distribution and travel patterns of the sampled taxis needs to be further examined when additional datasets become available. In addition, taxi usage can exhibit seasonal variations (e.g., more people may take taxis when it is snowing), which may not be captured by analyzing the particular dataset for three weeks in a March. Data with greater temporal coverage or multiple datasets collected at different time of the year could improve this study.

Additionally, one key assumption made in this research is that PHEV taxis exhibit the same travel pattern as ICE taxis. It is possible that PHEV taxis will change travel patterns to drive more on electricity and take advantage of the potential fuel savings. However, currently there is no data available to estimate the change of travel behaviors in response to adoption of EVs and this assumption is commonly made in other studies [37, 94].

Furthermore, this study does not take into consideration the space constraints and the capacity limits of the charging stations. Depending on the location of the existing gas stations, certain stations may be constrained by space, the number of charging posts, and the associated parking space it can accommodate. If all charging posts are occupied at a given time, nearby vehicles with charging needs will either need to wait in line and delay/reduce their charging time or have to go to a different station. With 500 charging stations, the maximum number of vehicles simultaneously charging at the same station can be up to 16 during peak hours. Considering that only 18% of the taxi fleet is included in this study, the competition for charging ports at popular stations can be a more significant problem for a fully electrified taxi fleet. Therefore, future studies need to include the “crowd out” effect in the model to better reflect vehicle charging behaviors.

Lastly, while the methodological framework developed in this study is applicable to other fleets and other cities, conclusions drawn in this study should not be generalized to private vehicles in Beijing or taxi fleets in other cities. This study assumes that charging stations are dedicated to taxis and the charging demand of private vehicles is not considered in the siting process. Travel trajectory data for private vehicles need to be collected and analyzed if the charging stations are designed to also serve private vehicles. In addition, when evaluating charging station candidates for private vehicles, the parking-lot-based approach should be used instead of the gas-station-based approach.

4.3.4 Contribution of Individual Travel Pattern Data

Aggregated travel pattern data present representative travel statistics (e.g., average VMT, trip length). However, there is no "representative" location for vehicle public charging; therefore aggregated travel pattern cannot be used to support charging station siting. As a compromise, indicators such as traffic volume and vehicle ownership have been used as proxy of charging demand. However, as discussed earlier, due to the difference between charging and refueling, these proxies do not necessarily represent charging demand. Individual travel pattern data enable modeling of charging needs for each individual vehicle at each specific location, which can be used to identify fleet level charging demand to site public charging stations.

The study conducted by Liu (2012) is the most related to this research because it also evaluates charging infrastructure planning for the city of Beijing [42]. Liu (2012) used the distribution of gas stations to represent geographical variations of charging demand and assigned home charging posts, public charging posts, and batter swap stations based on the locations of residential communities, gas stations, parking lots, and power transmission stations. Lacking individual travel pattern data, Liu (2012) made many assumptions for charging time, charger occupation rate, and charging demand allocation. In contrast, these parameters can be directly calculated from travel pattern data in this research. Charging stations sited in this research are more concentrated in the inner city while those in Liu (2012) are more spread out.

4.4 Summary

Using the taxi fleet in Beijing as a case study, this study examines large-scale vehicle trajectory data to study public charging station planning and potential environmental and power grid impacts from electric taxi fleet charging. The results show that: 1) public charging opportunities identified using collective vehicle parking events can be used as good indicators for public charging demand; 2) comparing to existing charging stations, the same amount of gas-station-based charging stations selected based on travel patterns can improve overall electrification rate by 37%, which can lead to gasoline displacement for the taxi fleet of up to 46.4 million gallon per year; 3) with current grid mix, CO_2, $PM_{2.5}$, PM_{10}, SO_2, and NO_x emissions will increase with higher electrification rate while CO emissions will decrease; and 4) power demand for public electric taxi charging has peak load around noon time, overlapping with Beijing's summer peak power, which means that charging time management techniques are potentially needed, especially for fast charging stations.

The optimization results further show that: 1) the optimal locations of charging stations can have significant improvements on electrification rate comparing to the existing ones and the suboptimal ones selected based on simple rules; 2) charging stations in Beijing should be first built in the inner city first and then expand outward; 3) while more charging stations increase electrified fleet VMT, the marginal gain diminishes quickly regardless of charging speed. The difference of electrified fleet VMT between the same number of slow and fast charging stations stays constantly at 20% with more than 40 charging stations; and 4) the majority of the stations selected in a model with smaller number of charging stations remain as the optimal choices when the total number of charging stations increases.

CHAPTER V

Environmental Benefits of Ride Sharing in Cities

5.1. Introduction

With over half of the global population now living in urban areas, urban sustainability is becoming increasingly important [154]. Vehicle transportation is a critical component of urban sustainability because it contributes significantly to energy consumption and emission generation. For example, the transportation sector accounted for 28% of total energy use and 27% of total GHG emissions in the U.S. in 2013 [6, 155]. As the economy grows and population increases in urban centers in developing countries, improving efficiencies in public transportation services and personal automobile uses can provide more cost-effective and environmentally friendly transportation solutions.

Sharing rides as a way to reduce transportation energy consumption is not new. As early as in the 19th century, the U.S. government has implemented policies to organize ride sharing (Car-Sharing Club) to conserve transportation fuel during World War II [49]. In addition to the societal benefits of reducing congestion, alleviating emissions, and conserving energy, ride sharing also offers benefits to the participants, which include lowering travel cost, gaining access to HOV lanes, and avoiding the search for parking. However, due to the lack of attractive market mechanisms, difficulties of arrangement, and safety concerns to ride with strangers [49, 50], ride sharing has largely been constrained to the small scale (e.g., with families, friends, and colleagues) and is mostly prearranged (e.g., airport shuttles, van pools) [51].

The recent development in ICT such as smartphones and various apps has enabled users to exchange information in real-time and makes participation in the “sharing economy” more feasible, both technically and socially. Technically, the availability of real-time rider travel information, such as trip origin, trip destination, and desired departure and arrival time, has made it possible to develop a dynamic ride sharing (a.k.a., real-time ride sharing) system which only requires minimal amount of lead time to identify sharing matches. Socially, the involvement of social networks and reputation systems to help build trust makes people feel more comfortable to share with strangers (e.g., Uber, Sidecar, Lyft, Airbnb) [53, 54]. Therefore, ICT-enabled real-time ride sharing presents unprecedented opportunities to improve urban transportation efficiency. The technology and cyberinfrastructure for dynamic ride sharing at the large scale has already partially existed. Several startup companies have already started to provide dynamic ride sharing services (e.g. Uberpool[1], Split[2]).

The current literature on ride sharing mainly focuses on developing efficient algorithms for rides matching and recommender systems [52, 57-61]. Limited attention has been paid to quantifying the “shareability” of travel demand at the city level, which is important to persuade investors to invest in and promote such systems [156]. This research aims to fill this gap to quantify the environmental benefits of ride sharing in urban cities, taking into account the heterogeneous individual travel demands.

Four types of data are currently used to study ride sharing: travel survey data, cellphone traces, geo-tagged social media data, and trip origin and destination data. Based on commuting survey data, Amey (2010) estimated that sharing rides can reduce commuting VMT by 6% to 19%

[1] https://get.uber.com/cl/uberpool/
[2] http://split.us/

for the Massachusetts Institute of Technology (MIT) communities [51]. Although travel survey data are best suited to serve the purpose of analyzing ride sharing at the small scale (e.g., commuting within the MIT community), the information provided by survey data is static and cannot be used to study dynamic ride sharing at the larger geographic scale. Using cellphone records and geo-tagged tweets, Cici et al. (2014) estimated that ride sharing with friends' friends can reduce the number of cars in a city by 31% [92]. However, cellphone traces and geo-tagged social media data have very coarse granularity because the geolocation data of a user are only recorded when the user makes a phone call or posts a tweet. Trips that occur between two consecutive phone calls or tweets cannot be captured and may lead to inaccurate travel demand inference. In a study that evaluated trip origins and destinations of taxi trips in New York City, Santi et al. (2014) concluded that sharing taxi trips can cut trip length by 40% or more [156]. Trip origins and destination data can more accurately describe the travel demand of each traveler and therefore can support large scale dynamic ride sharing analysis better.

Using trip origins and destinations extracted from the taxi trajectory data in Beijing, China as a case study, this research further evaluates the environmental benefits of shared taxis. Although ride sharing using private vehicles may be different from shared taxi rides, the framework and methods developed in this research can be applied to private vehicles when trip origins and destinations using private vehicles become available at the large scale. In addition, compared to ride sharing among private drivers, which requires more individual initiatives, shared taxi rides are more readily implemented.

5.2. Data and Methods

5.2.1 Data

Data used in this study are vehicle trajectory data for 12,083 taxis in Beijing from November 1 to December 1 in 2012. After data cleaning, the dataset includes a total of 894.5 million data points, covering 69.3 million miles of travel. Each data point includes a vehicle id number, operation status (occupied by passengers, parked, or unoccupied), a time stamp when a data point is recorded, the location of the taxi at the time of recording (longitude and latitude), GPS speed, GPS direction, and GPS status (whether the GPS device is functioning). The data are cleaned to remove scattered points that are outside of the main time span, duplicate points, and points that are shown as invalid according to the GPS status information. Vehicles with less than 27 days of data during the period of November 1 to December 1 in 2012 are also removed from the dataset. The origins and destinations of passenger trips are identified based on the taxi operation status. Locations where the operation status changes from other status (either parked or unoccupied) to occupied are identified as trip origins. Similarly, locations where the operation status changes from occupied to other status are identified as trip destinations. Trip distance is calculated as the summation of the Manhattan distances of each pair of consecutive points in the trip. The Manhattan distance, which measures the distance between two points (X_1, Y_1) and (X_2, Y_2) as $|X_1-X_2| + |Y_1-Y_2|$, can provide better estimates for the actual travel distance between two locations in a road network. A total of 5.2 million occupied trips are extracted.

5.2.2 Shared Rides Matching Analysis

In the shared rides matching analysis, I assumed that a maximum of two trip parties can share one taxi. This assumption is made because having more parties share a ride significantly complicates computation but only offers marginal ride sharing benefits [156]. The analysis includes two components: identification of all sharable trips and optimization of shared trips to maximize the total avoided VMT.

5.2.2.1 Identification of All Sharable Trips

For each trip i, the trip origin (O_i), trip destination (D_i), trip distance (d_i), departure time from trip origin (t_O_i), and arrival time at destination (t_D_i) are known. Trip i is sharable with another trip (e.g., trip j) if the shared trip ij can reduce total travel distance and only tolerably impact trip departure and arrival time for both trip parties in trip i and trip j. **Figure 5-1** presents the framework for sharable trip identification.

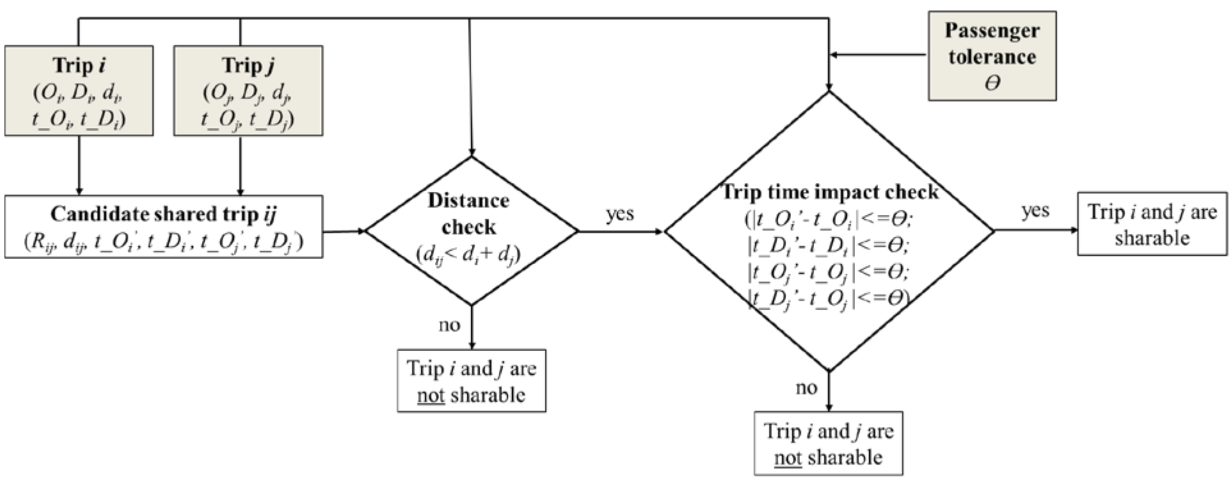

Figure 5-1. Framework for sharable trip identification

The candidate shared trip ij is identified as the route (R_{ij}) that can lead to the minimum shared trip distance (d_{ij}) among all possible routes. For sharing two trips, there are four possible route: O_i - O_j - D_i - D_j; O_i - O_j - D_j - D_i; O_j - O_i - D_i - D_j; and O_j - O_i - D_j - D_i. I do not consider trips without overlap (e.g., O_i - D_i - O_j - D_j) as sharable in this study. If the total distance of the candidate shared trip (d_{ij}) is less than that of the two individual trips ($d_i + d_j$), the candidate shared trip ij passes the distance check. Next, the travel time impact check examines whether the deviations of trip departure and arrival time are tolerable to passengers in both trips. I assumed that both early departure and trip delay can equally cause inconvenience to the passengers. The passengers have a pre-specified tolerance level (Θ, in minutes), indicating their flexibility in of the deviations of departure and arrival time caused by ride sharing. Only when the deviations of trip departure and arrival time are within the tolerant level for passengers in both trips, the candidate shared trip passes the trip time impact check. In this study, I assumed that all passengers have the same tolerance level and the tolerance level for both early departure and trip delay is the same. The default tolerance level is 10 minutes. This value is chosen based on Li et al. (2007) which reported that over 75% of the carpool participants they surveyed spent less than 10 minutes for carpool formation [56]. The impacts of different tolerance levels are examined in the sensitivity analysis in **Section 5.3.2**. This study also assumed a 1 minute passenger loading/debussing time to account for the time required for the taxis to slow down, stop, and for the passengers to get on and off.

To calculate the departure and arrival time at each origin and destination locations for the shared trip, I assumed that the travel speed for the portion of the shared trip that deviates from the original trips to accommodate for ride sharing (e.g., pick up the second passenger) is the average of the travel speeds for the individual trips. I also assumed that ride sharing will not impact the traffic conditions for the portion of the shared trip that is identical to one of the original trips. Equations (1) to (7) present an example of travel time calculation for the route O_i - O_j - D_j - D_i.

$$v_i = d_i/(t\_D_i - t\_O_i) \quad (1)$$

$$v_j = d_j/(t\_D_j - t\_O_j) \quad (2)$$

$$v_{ij} = (v_i + v_j)/2 \quad (3)$$

$$t\_O_i' = t\_O_i \quad (4)$$

$$t\_O_j' = t\_O_i + dist(O_i - O_j)/v_{ij} \quad (5)$$

$$t\_D_j' = t\_O_j' + (t\_D_j - t\_O_j) \quad (6)$$

$$t\_D_i' = t\_D_j' + dist(D_j - D_i)/v_{ij} \quad (7)$$

where v_i, v_j, and vij are the average travel speeds for trip *i*, trip *j*, and shared trip *ij*; t_O_i', t_D_i', t_O_j', t_D_j' are the departure and arrival time in a shared trip for passengers from trip *i* and trip *j*, respectively; t_O_i, t_D_i, t_O_j, t_D_j are the departure and arrival time for individual trip *i* and trip *j*, respectively; and $dist(O\text{i} - O_j)$ and $dist(D_j - D_i)$ are the distances between trip origin locations for the two shared trips and the distances between the trip destination locations for the two shared trips.

The travel distance of a trip is normally greater than the Manhattan distance between the trip origin and destination (**Figure 5-2**) due to required extra travel (e.g., extra distance traveled to get onto a highway or detour due to one-way streets). Therefore, I estimated trip travel distance in the portion of the shared trip that deviates from the original trips to accommodate for ride sharing based on the relationship observed in **Figure 5-2**. For example,

$$dist(O_i - O_j) = 1.163 * MD(O_i, O_j)+0.293 \quad (8)$$

where $MD(O_i, O_j)$ is the Manhattan distance between point O_i and O_j.

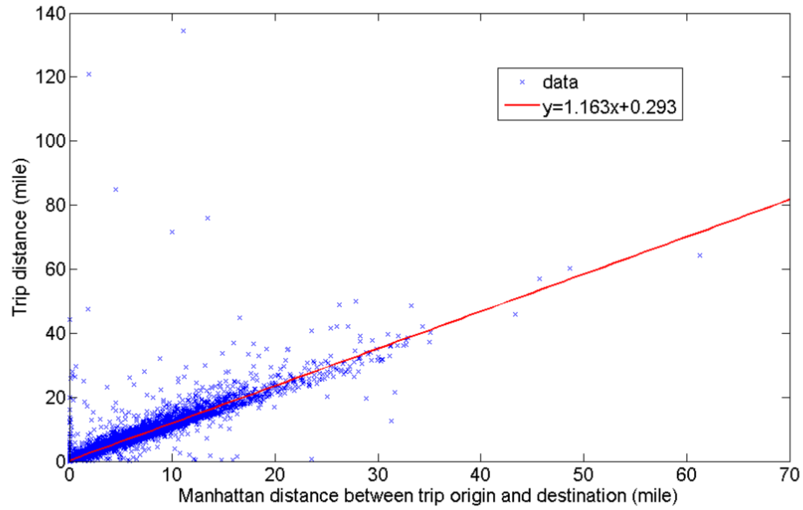

Figure 5-2. Relationship between trip travel distance and Manhattan distance between trip origins and destinations (R^2 = 0.775 for the fitted line)

Only when the candidate shared trip passes both of the distance and trip time impact checks, the two trips are identified as sharable. I identified all sharable trips that meet the above criteria. The outputs of this component are two n-by-n matrices A and S with n being the total number of trips. A_{ij} equals to 1 if trips *i* and *j* are sharable and equals to 0 otherwise. S_{ij} equals to the VMT that can be saved by sharing trip *i* and *j* if A_{ij} is 1 and equals to 0 otherwise.

5.2.4.2 Optimization

The pairs of rides to be shared are then identified to maximize the total VMT savings.

The objective function is to max $\sum_j \sum_i L_{ij} \times S_{ij}$ (9)

Subject to:

$\sum_i L_{ij} \leq 1$ (10)

$\sum_j L_{ij} \leq 1$ (11)

$L_{ij} \leq A_{ij}$ (12)

$$L_{ij} \geq 0 \qquad (13)$$

where L_{ij} equals to 1 when trip i and j are shared and equals to 0 otherwise.

5.2.3 Emission Factors

To calculate the emission reduction from ride sharing, the following well-to-tank emission factors for gasoline vehicles are used: 0.28 g/mile for VOCs, 0.3 g/mile for NOx, 0.08 g/mile for PM10, 0.038 g/mile for PM2.5, and 3.6 g/mile for CO [31].

5.3. Results and Discussion

5.3.1 Sharing Benefits

Regardless of the variations in the total number of trips accrued during the day, the ride sharing benefits (miles saved and trips shared) are relatively stable (**Figure 5-3**). On average, about 77% of the trips can be shared, leading to 33% of the total VMT saved. The day-to-day variances of hourly sharing benefits are also relatively small, regardless of weekdays and weekends. These results indicate that the travel patterns of taxi riders in Beijing offer consistent high sharability. Based on the average daily VMT saved, I then calculated the daily criteria emissions reduced due to ride sharing (**Figure 5-3**). Scaling up to the entire taxi fleet over the entire year, shared taxis can reduce 186 tons of VOC, 199 tons of NOx, 53 of tons PM10, 25 tons of PM2.5, and 2,392 tons of CO emissions annually. Based on the annual on-road vehicle emission in Beijing estimated in [157], the shared taxi trips can reduce total NOx, PM10, and CO emissions by 0.24%, 1.4%, and 0.28%, respectively.

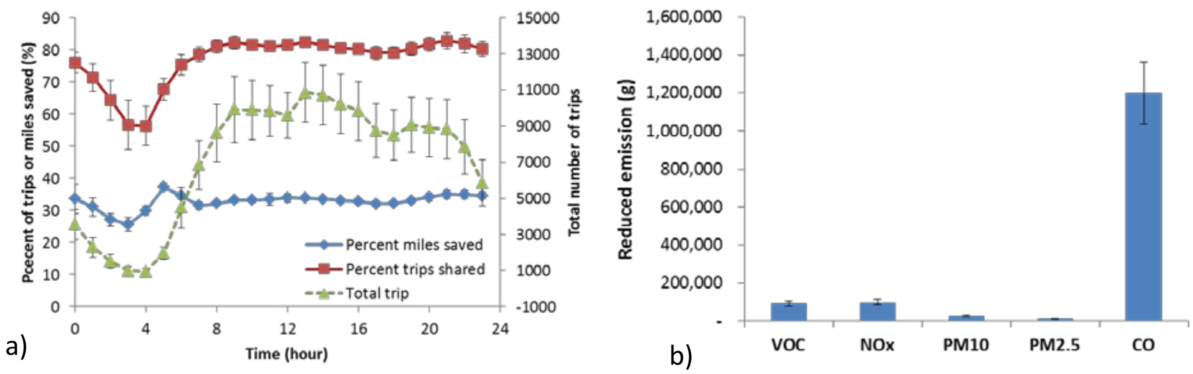

Figure 5-3. Ride sharing benefits. a) Hourly trip VMT saved and shared trip percentages comparing to the number of total trips. b) Daily avoided criteria pollutants.

5.3.2 Impact of Tolerance to Trip Time Deviation

Sharing benefits are most sensitive to rider's tolerance level to trip time change (Θ). The sensitivity analysis shows that it does not require too much tolerance from riders to enable ride sharing (**Figure 5-4**). As long as the riders can tolerant a trip departure or arrival time change of four minutes, 60% of the trips departing between 8am to 8:59am can be shared with 20% of the VMT saved.

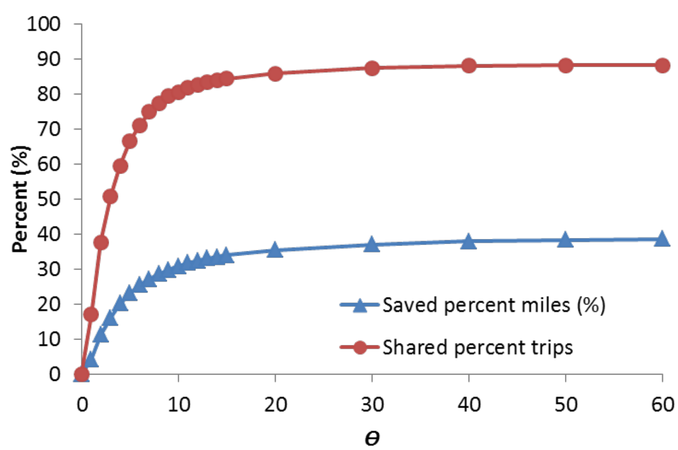

Figure 5-4. The impact of rider's tolerance level of trip time change (ϴ) to sharing benefits for trips departing between 8am to 8:59am.

5.3.3 Limitations and Future Research

First, trip sharing opportunities are only evaluated using hourly data according to trip start time (e.g. trips start between 8:00am an 8:59am as a group). The use of hourly data limits the sharing possibilities of trips that depart close to the cut-off time. For example, a trip that departs at 7:59am cannot be shared with a trip that departs at 8:01am. Implementing a sliding window can cover the potential sharing opportunities better.

In addition, in the process of identifying sharable trip, I assumed that ride sharing has a minimal impact on traffic conditions in the road network for calculating trip time deviation. This assumption needs to be further validated. If ride sharing can help increase average travel speed on a congested road, ride sharing can provide additional benefits in improving the fuel economy and lowing air emissions of the whole on-road fleet. The increased travel speed can also help reduce trip delays due to ride sharing and make more trips sharable. On the hand, however, picking up and dropping additional passengers requires the taxis to stop multiple times during a trip, which can increase emissions due to the increased deceleration and acceleration.

Furthermore, when scaling up the emissions reduction from ride sharing from the sampled taxis to the entire fleet, I assumed that the percent of VMT that can be saved stays the same. With more vehicles and travel demands, it is possible for the ride sharing benefits to increase with more riders (e.g., trips currently cannot be shared can then find a match). The relationship of ride sharing benefits and the total number of riders needs to be further explored.

It is also notable that the emission reductions in this study are based on average emission factors. Driving conditions (e.g. travel speed and acceleration) and ambient environment (e.g. cold or hot weather which results the use of heating and AC in the vehicle) can also affect vehicular emissions. More detailed modeling of emissions considering these factors can improve this analysis.

Lastly, the rebound effect is not considered in this research. Shared taxis can free taxi capacities and reduce taxi fares which may motivate more people to take taxis. If these additional taxi riders are diverted from users of the public transit systems, the environmental benefits of ride sharing can be undermined as a result of the rebound effect [158].

5.3.4 Contribution of Individual Travel Pattern Data

Evaluating the potential for ride sharing requires detailed information on trip origins, destinations, and travel time, which cannot be obtained from aggregated travel data. Without individual travel pattern data, previous studies have used assumed distributions of home and work locations to estimate the benefits of shared commuting trips [159]. However, these assumed distributions may not reflect real world conditions and can underestimate the sharaeability of trips [92].

5.4 Summary

Using shared taxis in Beijing as an example, this study evaluates the environmental benefits of ride sharing. Shared taxis can provide stable sharing benefits in total VMT and emissions reduction, regardless of the travel volume and daily travel pattern variations. With a rider’s tolerance level at 10 minutes, ride sharing can reduce fleet VMT by 33%. If implemented for the entire taxi fleet, shared taxis can reduce 186 tons VOC, 199 tons NOx, 53 tons PM10, 25 tons PM2.5, and 2,392 tons CO emissions annually. Although the sharing benefits significantly depend on riders’ tolerance level to trip time deviation, not much tolerance is required to gain significant ride sharing benefits.

CHAPTER VI

Conclusions

Through three case studies (vehicle electrification, charging infrastructure siting, and ride sharing), this research demonstrates that integrating individual travel patterns into environmental assessments can enhance our understanding of the environmental implications of these emerging transportation systems and better support decision making. Based on the results of this research, following major conclusions can be drawn.

1. Vehicle trajectory can be integrated into environmental assessments to capture individual travel patterns.

Vehicle trajectory data collected by GPS devices are proved to be helpful in capturing travel patterns for each individual vehicle, which can be used to better analyze charging behaviors and ride sharing potentials in environmental assessments. Compared to travel survey data and other types of big data on personal mobility (e.g., geo-tagged social media data, cellphone records), vehicle trajectory data have the advantages in large sample size, more accurate location information, known transportation mode, inferable travel route, and high spatiotemporal resolution. However, vehicle trajectory data normally do not contain social-economic and demographic information of the drivers and the transportation mode is apparently limited to vehicles. Therefore, when studying more complex systems (e.g., multi-model transportation), a combination of different types of data may be required.

2. Individual travel patterns can impact the environmental performance of fleet electrification. When unit battery cost exceeds $200/kWh, vehicles with greater battery range may not promote more travel electrification and can even reduce electrification rate.

The case study of Beijing taxi fleet electrification (Chapter III) shows that individual travel patterns can significantly influence the adoption and utilization of EV and therefore determine the potential environmental benefits of electrifying the taxi fleet. At the current battery cost ($400/kWh), medium range PHEV with around 90 miles AER can provide the highest travel electrification and oil displacement for the fleet. Because PHEVs with larger battery range are too expansive for adoption based on the observed travel patterns, larger battery range can reduce electrification rate. This mechanism cannot be captured if using aggregated travel pattern data. Previous studies show that utility factors of PHEV either monotonously increase with battery range or flatten out.

3. Individual travel patterns can guide public charging infrastructure development. Charging stations sited according to individual travel patterns can electrify more VMT.

Traditional approaches used to estimate refueling demand (e.g., traffic density, vehicle ownership) cannot appropriately represent public charging demand for EV system, because charging takes longer than refueling and may also happen at home. The case study of charging station siting using vehicle trajectory data (Chapter IV) demonstrates that the collective vehicle parking pattern can be a good indicator for charging demand and provide better basis for modeling charging behaviors. Better matching of charging stations and charging demands can achieve higher fleet level travel electrification. Compared to the existing 40 stations, selected optimal gas-station-based charging stations can improve the electrification rate by 59% and 88%

with slow and fast charging, respectively. Without using travel pattern data, previous studies had to make many assumptions for charging time, charger occupation rate, charging demand allocations etc. These parameters can be directly calculated from individual travel pattern data in this research.

4. Trip details extracted from vehicle trajectory data enable dynamic ride sharing modeling. Shared taxi rides can reduce total travel distance by 33% with 10-minute travel time deviation tolerance.

Evaluating the potential environmental benefits of dynamic ride sharing requires detailed travel demand information, which can be extracted from vehicle trajectory data. Results from the case study of taxi ride sharing (Chapter V) indicate that ride sharing can provide stable benefits in total VMT saving and emissions reduction. It only requires the riders to have a minimal tolerance level to trip time deviation (4 minutes and above) to achieve significant reduction in total travel distance (20% or more). Without individual travel pattern data, previous studies are either limited to the small scale (e.g. in a community) or have to assume distributions of trip origins and destinations. Vehicle trajectory data provide more accurate information to assess the shareability of trips and the associated environmental impacts.

Future Research

This research has the following limitations which also provide directions for future research. First, this study assumed that the data collected for the over 10,000 taxis are representative for the entire taxi fleet (approximately 66,000 taxis). Although no specific biases are observed in the data, this assumption needs to be verified using additional datasets. While it is ideal to have data for the entire population, the computational cost will also increase.

Therefore, an interesting question for future research is how much data is required to describe the collective travel pattern while preserving the individual heterogeneity.

In addition, using historical travel data to study emerging transportation systems assumes that people will not change their behaviors. While this assumption has been made by many relevant studies, the impact of potential behavior change needs to be further explored. EV drivers can actively seek charging opportunities to save fuels, leading to higher percentage of electrified travel than expected. Reduced taxi fares due to ride sharing can potentially divert public transit users to take taxis which may reduce the environmental benefits of ride sharing.

Furthermore, this study evaluates the electric vehicle systems and ride sharing systems separately. These systems can also be integrated, such as shared electric taxis. The integrated systems can cause behaviors change and have different system optimal solutions. For example, with ride sharing, the resting time (and charging opportunities) for electric taxis can potentially be increased due to elimination of unoccupied trips searching for customers or decreased due to longer trips delivering multiple customers. The change of travel patterns can also affect charging demands and the optimal locations for charging stations. Future studies can analyze such integrated systems by combining the different models developed in this research.

The models developed in this study can also be expanded to evaluate other objective functions. In addition of the electrification rate used in this study, other potential objective functions include total emission or emission reduction (for GHG or a particular criteria pollutant), human health impact, water impact, energy consumption etc.

Lastly, the case studies only used data from one particular type of fleet in a specific city. While the methods and framework developed in this research is generally applicable to other fleets and cities, the conclusions cannot be directly generalized to private vehicles or fleets in other cities. Private vehicles may have very different travel patterns from taxis. Urban infrastructure also impacts vehicle travel patterns in different cities. Therefore, additional research on travel patterns of individual private vehicles and comparison among multiple cities will provide valuable information for decision making in sustainable urban transportation systems.

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