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Migrating towards Using Electric Vehicles in Fleets – Proposed Methods for Demand Estimation and Fleet Design

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To the Graduate Council:

I am submitting herewith a dissertation written by Taekwan Yoon entitled "Migrating towards Using Electric Vehicles in Fleets – Proposed Methods for Demand Estimation and Fleet Design." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

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Migrating towards Using Electric Vehicles in Fleets – Proposed Methods for Demand Estimation and Fleet Design

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Taekwan Yoon

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I would like to dedicate my dissertation
to Jesus Christ
and
my parents, Young-hyun (Raphael) Yoon and Youn-ja (Kristina) Choi

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ABSTRACT

Carsharing and electric vehicles have emerged as sustainable transportation alternatives to mitigate transportation, environmental, and social issues in cities. This dissertation combines three correlated topics: carsharing feasibility, electric vehicle carsharing fleet optimization, and efficient fleet management. First, the potential demand for electric vehicle carsharing in Beijing is estimated using data from a survey conducted the summer of 2013 in Beijing. This utilizes statistical analysis method, binary logit regression. Secondly, a model was developed to estimate carsharing mode split by the function of utilization and appropriate carsharing fleet size was simulated under three different fleet types: an EV fleet with level 2 chargers, an EV fleet with level 3 chargers, and a gasoline vehicle fleet. This study also performs an economic analysis to determine the payback period for recovering the initial EV charging infrastructure costs. Finally, this study develops a fleet size and composition optimization model with cost constraints for the University of Tennessee, Knoxville motor pool fleet. This will help the fleet manage efficiently with minimum total costs and greater demand satisfaction. This dissertation can help guide future sustainable transportation planning and policy.

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1 INTRODUCTION

This study focuses on improved transportation options that combine carsharing with electric vehicles. Carsharing is a car rental program where people may rent cars for short periods, usually by the hour. Potential advantages of carsharing programs include cost benefits, transportation efficiency, and environmental improvements. An electric vehicle (EV) is a battery-powered vehicle. It is considered a sustainable transportation mode because EV emits less greenhouse gas than a gasoline vehicle. This does not preclude emissions from an electric power plant (Funk and Rabl 1999, Taylor, Maitra et al. 2009).

First, this study investigates the market potential for carsharing systems in Beijing, with a focus on price, performance, and vehicle attributes. It investigates EV potential, the role of weather, air quality, and even "status" indicators. The study relies on a pen-and-paper survey that allows a pivoting design to merge revealed preference (RP) and stated preference (SP) components. In the summer of 2013, the survey--which includes 1,010 completed survey forms with 2,023 reported trips--was conducted in the seven main districts of Beijing. The survey data was used to build a binomial logit regression model to analyze choice models influenced by different variable sets.

Secondly, this study helps target markets and estimate potential demand for carsharing (mode split) with the utility function. It estimates fleet size based on the estimated carsharing mode split from realistic scenarios including three fleet types: an EV fleet with level 2 charging infrastructure, an EV fleet with level 3 charging infrastructure, and a gasoline vehicle fleet. The simulation method is used with factors such as vehicle types (electric or gasoline vehicle), charger types for EVs (level 2 or level 3 chargers) that influence charging time, arrival rates, travel distance, and travel time based on the time intervals (peak or non-peak hours). Furthermore, an economic analysis was performed to include costs associated with infrastructure, vehicle depreciation, maintenance, fuel, and revenue.

Finally, this study focuses on efficient fleet management that addresses demand with cost constraints. This research will focus on the heterogeneous fleet optimization with travel distance and recharge time constraint for EVs. The developed fleet size and composition optimization model contributes to fleets by helping determine fleet size and the EVs adoption. The model and the program are flexible enough to be used in a wide variety of fleet optimization problems.

The rest of this research is organized as follows. In Chapter 2, we will study about EV carsharing feasibility in Beijing, China. In Chapter 3, we will focus on carsharing fleet optimization through a mode choice model, a simulation, and an economic analysis. In Chapter 4, we will show how to optimize fleet size and composition for the University of Tennessee motor pool fleet. Finally, the conclusions of the research will be presented in chapter 5.

2 INVESTIGATING THE FEASIBILITY OF ELECTRIC VEHICLE (EV) CARSHARING: A CASE STUDY OF BEIJING, CHINA

ABSTRACT

This study examines the market potential for carsharing systems in Beijing. Carsharing is a car rental program where people may rent cars for short periods, usually by the hour. Potential advantages of carsharing programs include cost benefits, transportation efficiency, and environmental improvements. This study also investigates the potential for electric vehicle use in the carsharing system as well as how weather, air quality, price, vehicle attributes and even "status" indicators could impact the carsharing system. It relies on a pen-and-paper survey (1,010 completed survey forms with 2,023 reported trips) that allows a pivoting design to merge revealed preference (RP) and stated preference (SP) components. The survey data was used to build a binomial logit regression model for one-way carsharing and a round trip. In the results, age, gate apartment residence, car ownership, the comfort index for subway users, shelter mode, the original cost for taxi users, perceived parking availability, and weather factors were significant for one-way carsharing. For round trip carsharing services, significant factors include car ownership, income, gender, environmental concern, and the cost gap. The most significant factors to attract carsharing customers are cost gap (defined as cost of original **–** cost of carshare) for both one-way and round trip carsharing services and car ownership that shows positively significant for one-way and negatively significant for round trip carsharing service. Air quality and peak-time travel were not significant for carsharing choices. This paper contributes to the literature by further examining carsharing feasibility and developing models that can be applied in urban environments like Beijing, China.

2.1 INTRODUCTION

Recently, urban population increases and registered vehicle increases have exacerbated cities' transportation and environmental issues (Banister, Anderton et al. 2011). To alleviate these problems, cities have tried transportation demand management strategies including parking management, improved transportation options, vehicle registration quotas, license plate based travel restrictions, and incentives to use alternative modes or reduce driving. Parking management could entail priority parking for carpools or institutional reforms such as the Commute Trip Reduction Act (CTR) (Seattle Urban Mobility Plan 2008). Improved transportation options may include biking, walking, transit, and ridesharing encouragement. Incentives to use alternative modes and reduce driving could include universal transit passes, flexible work schedules, road pricing, and alternative fuel vehicle subsidies. This study focuses on improved transportation options by examining carsharing and electric vehicles (EV) as a travel demand mechanism while also providing low-emitting motorized options.

Carsharing is a car rental program where people may rent cars for short periods, usually by the hour or kilometer. Carsharing was first introduced in Zurich, Switzerland in 1948 (Truffer March 1998). Since then the most successful and recent carsharing programs began in Europe in the mid-1980s. The most active countries (Switzerland, Austria, the Netherlands, and Germany) each boast more than 100,000 participants. Across the Atlantic, a research program at Purdue University from 1983 to 1986 developed the first carsharing company in North America. Currently forty two carsharing organizations exist in North America (Martin and Shaheen 2011) with the three largest providers in the United States and Canada supporting almost all carsharing membership (Shaheen, Cohen et al. 2006). Carsharing is largely a feature of transportation systems in industrialized countries. Most carsharing activities occur in North America and

Europe(Shaheen, Sperling et al. 1998, Lane 2005, Shaheen, Cohen et al. 2006, Shaheen and Cohen 2007, Shaheen, Cohen et al. 2009, Martin, Shaheen et al. 2010, Shaheen, Rodier et al. 2010).

Carsharing programs can potentially offer cost advantages, transportation efficiency, and environmental improvements. Carsharing provides some of the benefits of private car ownership while spreading costs across multiple users and trips, thereby decreasing the cost of car use while improving the utilization of the vehicles (Shaheen and Martin 2006). Carsharing provides members with access to a vehicle without individual ownership costs (Shaheen, Meyn et al. 2003). Most ownership costs are from depreciation which is incurred regardless of the amount of vehicle use (American Automobile Asociation 2013). After the initial purchase and sunk costs for registration and insurance, personal car ownership has relatively low variable costs which encourage frequent driving (Shaheen and Martin 2006). In contrast, a vehicle will be used as needed by low-income households and other car-less households (Creutzig and He 2009).

Car owners drive more frequently than carshare participants. Carsharing reduces personal car ownership and subsequent VMT. As carshare users increase, the average number of vehicles owned in households decreases. In Europe, each carshare vehicle replaces approximately 4-10 vehicles; 15-34% of European carsharing participants sell their private vehicles after joining a program. In North America, each carshare vehicle replaces approximately 6-23 vehicles; 11-29% of North American carsharing participants sell their private vehicles after joining the program. It also increases of the number of people who postponed or avoided a vehicle purchase (Cervero and Tsai 2004, Shaheen and Cohen 2007). Decreased ownership and VMT reductions help mitigate road congestion and encourage transit ridership (Cervero and Tsai 2004, Cervero, Golub et al. 2007, Martin, Shaheen et al. 2010).

However, carsharing still results in personal vehicle use and the accompanying environmental impacts. Alternative fuel vehicles are uniquely suited for carsharing. Unlike a household that may be burdened by the higher purchase price and charging infrastructure cost for alternative fuel vehicles, a carsharing company can benefit from the long-term cost of ownership savings. It can internalize higher capital costs such as purchase price and infrastructure cost into small changes in rates. EV would be one alternative in a carsharing system. Due to zero tailpipe emission and a silent motor, the emission from EV usage can be less than that of conventional gasoline vehicle (CV) (Funk and Rabl 1999, Delucchi, Yang et al. 2014). EV adoption helps reduce dependence on imported oil (Thomas 2009). Moreover, carsharing companies would provide customers with a fleet of vehicles to choose from, so they can often choose the most efficient vehicle for each trip. For example, small EVs would be used for short trips; CVs would be best for longer trips; trucks would be needed for moving goods; and so on. Carsharing systems allow users to select from a range of vehicles and their corresponding fuel types.

Currently, few developing countries have established carsharing systems with infrastructure; although China can be categorized as a developing country because of its recent and rapid economic development, carsharing has significantly increased in Asian countries since 1990s (Shaheen and Cohen 2007), including China. China has 1.3 billion people, 19.1% of the world's population. The population density of China is 365 people per square mile, but cities are much more dense. In Beijing, the population density is 12,800 people per square mile. As the city continues to expand, environmental conditions are deteriorating because economic growth and environmental quality goals often conflict.

Since urban cities in China are suffering from congestion and pollution due to an increasing population, the number of vehicles registered, and the vehicle miles traveled, this study aims to

analyze the feasibility of carsharing programs with CVs and EVs. The objective of this study is to identify the factors influencing an individual's decision to switch to carsharing through a stated preference experiment implemented in Beijing, China in the summer of 2013. The primary goals are 1) to understand the willingness of Beijing's residents to use carsharing systems and how different attributes of carsharing are valued by potential users 2) to identify the market acceptance of introducing EVs in a carsharing system and 3) to assess attributes related to status and image that are associated with car ownership and use. The rest of this paper is organized as follows: the background of carsharing and EV policies is shared along with Beijing's transportation and environmental challenges; the survey design, data collection, and modeling methodology is discussed; discrete choice models are presented and discussed along with survey results; concluding comments and recommendations for future research follow.

2.2 BACKGROUND

2.2.1 Carsharing benefits

Previous research concluded that carsharing can satisfy non-car owners' social and leisure needs while reducing travel costs. This is because the carsharing system can spread fixed ownership costs, including purchase price, registration and title fee, insurance, depreciation, and maintenance fees among many users (Shaheen, Sperling et al. 1998). Regardless of how much a car owner drives, approximately 77% of ownership costs are sunk in capital, registration, and insurance (Litman 2000). User cost savings of switching to carsharing can be significant. Present and ex-car owners saved between $680 and $780 per month in Singapore, where personal car registration fees are very high (Tuan Seik 2000). Another study examined participants of PhillyCarShare, a carsharing program in Philadelphia, Pennsylvania. About 40% of PhillyCarShare survey respondents stated that they have saved money and estimated an average

annual saving of $2,059 (Lane 2005). A first-year evaluation of CarSharing Portland reported that estimated cost savings was $154 per month per user, and Zipcar reported that carshare users can save an average of $435 per month by replacing vehicle ownership with carsharing (TCRP September 2005).

Furthermore, carsharing helps mitigate parking and traffic congestion in urban cities because carshare users are more likely to sell their private vehicles and cancel or postpone vehicle purchase plans. Since the 1980s numerous studies have examined how carsharing impacts vehicle ownership. Several European countries have reduced car ownership through carsharing. The ongoing program in Denmark states that one carsharing car replaces 4.6 to 6.2 private vehicles (Olsen 2006). In North America and Europe, an average of 21% of carsharing members reported giving up their vehicles. From another North American carsharing member survey, around 70% of the respondents postponed buying another car for their household and 11% sold their cars after they joined the carsharing program (TCRP September 2005). Since the primary expense for owning a private vehicle is fixed costs, owners drive more frequently with relatively low marginal costs. On the other hand, the carshare users drive less because fixed costs are averaged and charged at the margin, making each trip more expensive. This reduces travel demand and potentially reduces congestion in urban cities.

Carsharing can mitigate transportation issues in urban cities. For example, it reduces travel demand and thus is associated with fewer traffic accidents (Creutzig and He 2009). In addition, since carsharing vehicles often require dedicated parking spaces, which can also be used as a charging station for EVs, carsharing helps people save time to find parking spots in congested urban cities. Moreover, carsharing increases transit ridership and promotes transit-oriented

development because of combined transit/carsharing trips to access carsharing stations from origins (TCRP September 2005).

Lower peak travel demand and VMT also contribute to lower transportation emissions. Reduced emissions and better fuel economy can be expected because carsharing fleets can efficiently use alternative-fuel vehicles, replace old vehicles, and use smaller cars. For example, most carsharing companies offer hybrid-EVs, with lower emission rates of conventional pollution and GHG (TCRP September 2005). There are not many studies presently available to directly determine the environmental impact and improvement from carsharing, but it is clear that increased transit ridership, transit oriented development, and reduced ownership and VMT factors from carsharing contribute to environmental improvements (Steininger, Vogl et al. 1996, Meijkamp 1998).

Beyond these benefits, there are social benefits by offering vehicle access to low-income households and other car-less households (Creutzig and He 2009). There have been numerous studies related to who is attracted to carsharing (Burkhardt and Millard-Ball 2006), where does carsharing work (Celsor and Millard-Ball 2007, TCRP September 2005), what are the current carsharing programs (Shaheen, Sperling et al. 1998, Shaheen, Meyn et al. 2003, Cervero and Tsai 2004, Lane 2005, Shaheen and Novick 2005), how carsharing impacts a household (Litman 2000, Martin, Shaheen et al. 2010), what is its market potential in some countries including the US, European, and Asian countries (Shaheen, Sperling et al. 1998, Barth, Shaheen et al. 2006, Shaheen and Martin 2006, Shaheen, Cohen et al. 2009, Wang, Martin et al. 2012). This study recognizes the need for carsharing feasibility studies that address controlled experimental attributes like vehicle types, brandings, weather, air quality, access times, and cost structures for

both one-way and round trips. This research is based on actual travel behavior with data collected from a survey.

2.2.2 Electric vehicle

In general, an EV is a battery-powered vehicle recharged solely or in part by an external electrical source (i.e., plugged in). Since large batteries are required to supply energy, electric car design aims to make lightweight vehicles that counter the higher battery weight and minimize energy requirements. The practical driving distance of EVs is typically lower than an equivalent CV (Lester B. Lave 1995).

EVs can be an alternative mode of transportation and may reduce greenhouse gas emissions, local air pollution, and the dependence on imported petroleum (Taylor, Maitra et al. 2009) because EVs have no tailpipe emissions and use electricity as a fuel, which can be generated by clean sources. Still, EVs emit pollution from the electricity generating sector. The electricity costs depend on the site and nature of the pollution source (Funk and Rabl 1999).

EVs can reduce total cost of ownership for users compared to CVs (Shiau, Kaushal et al. 2010). Despite the 170% higher purchase cost, operating costs are generally a fifth lower because of reduced fuel costs (electricity vs. gasoline) and maintenance costs are lower. Over the economic lifecycle of a vehicle, EVs can break even with CVs after approximately 45,000 miles (depending on the cost of fuel). Unfortunately, consumers highly discount future fuel savings and see the high purchase price as a major barrier to adoption (Gallagher and Muehlegger 2011). Sharing EVs can reduce this barrier by providing higher utilization rates and more km per year, where fuel savings cause the vehicle to reach the break-even point sooner. The higher capital cost can be averaged and charged across the marginal use of the vehicle as a per kilometer rate.

Thus, carshare companies can benefit from providing vehicles with lower total cost of ownership and users can benefit from using EVs without high purchase price barriers.

Although there has been a great deal of research about relations between EVs and environmental impact (Lester B. Lave 1995, Rahman and de Castro 1995, Hackney and de Neufville 2001, Sims, Rogner et al. 2003, Jaramillo, Griffin et al. 2007, Ji, Cherry et al. 2011), cost benefit analysis (Funk and Rabl 1999, Delucchi and Lipman 2001, A.Simpson 2006, Hidrue, Parsons et al. 2011, Hao, Wang et al. 2013), life cycle analysis (Delucchi and Lipman 2001, Hackney and de Neufville 2001, Jaramillo, Griffin et al. 2007, Varun, Bhat et al. 2009), and potential impact (Kevin Morrow 2008, Wirasingha, Schofield et al. 2008, Bradley and Frank 2009, Hadley and Tsvetkova 2009, Taylor, Maitra et al. 2009, Ji, Cherry et al. 2011, Zheng, Mehndiratta et al. 2012), there is little research investigating EV adoption in carsharing fleets. This paper explores EV carsharing feasibility in Beijing.

2.2.3 Transportation and environmental challenges in Beijing

Beijing is considered the most congested city in China (Anas, Timilsina et al. 2009). It has a well-developed road and subway system. Its road network is composed of five ring roads with a total of 13,120 miles. In 2013, 1.51 billion passenger trips occurred in Beijing; 93% of those trips occurred by highways (National Bureau of Statistic of China 2011). In 2010, 3.74 million vehicles were privately registered. That was 25% more than the previous year despite of efforts to limit car usage through license plate restrictions. The license plate quota system limited the number of new vehicle registrations each year (Mike Hanley 2011).

Beijing has a well-developed subway system; 16 lines cover 275 miles with 261 stations. The city predicts daily ridership will increase to over 8 million trips per day, and the network will be

expanded to 19 lines covering 349 miles by 2015. More than 28,343 buses carried over 13.19 million person trips per day (Lei 2012). There are approximately 66,000 taxis with 6.5% mode split in Beijing estimated from the 2013 household survey statistics.

Beijing's air quality makes it one of the world's most polluted cities (Anas, Timilsina et al. 2009). Significant energy consumption increases since the 1980s have left Beijing with severe air pollution problems. The major emission sources are domestic heating, traffic, industry, dust, and biomass burning. Air pollution from the transportation sector is a growing portion of overall air quality challenges because the number of vehicles in Beijing has grown rapidly relative to other pollution sources (Im 2012). In 2012, the average Particulate Matter (PM) concentrations were 90 ppm (Finamore March 1, 2013), compared to the World Health Organization's interim targets-2 of 50 ppm for PM 10 and 25 ppm for PM 2.5 for annual mean concentrations (WHO 2005). The World Air Quality.info (AQI) and Insdio Production provides a real-time Air Quality Index (AQI) for Chinese cities. There are six categories: Good, Moderate, Unhealthy for sensitive groups, Unhealthy, Very unhealthy, and Hazardous based on health implications. These categories correspond to different concentrations of AQI number, which is the combination of $PM_{2.5}$, PM_{10}, O_3, NO_2, and SO_2 pollutants. The amount of pollution being created by vehicles in Beijing is a serious problem.

This research explores carsharing potential as well as possible environmental benefits of carsharing and EVs in Beijing's seven districts. There are currently few carsharing companies in Beijing and the business scales (sizes) are relatively small in comparison to other active countries. This study investigates the potential of widespread introduction of carsharing in Beijing, including integrating EVs. Through a survey it analyzes carsharing potential. Then it helps to

plan successful and efficient EV carsharing adoption in Beijing before widening the scope to other cities.

2.3 METHODOLOGY

The primary objective of this study is to investigate the market potential for carsharing systems in Beijing, with a focus on price, performance, and vehicle attributes. The study relies on a pen-and-paper survey that allows a pivoting design to merge revealed preference (RP) and stated preference (SP) components due to tight time and budget constraints (Campbell, Cherry et al. 2014). Pivoting creates a SP choice set with the new transportation mode, carsharing. It is based on respondents' RP results such as real travel behaviors (Hess, Rose et al. 2008, Rose, Bliemer et al. 2008, Train and Wilson 2008). This also quantifies the effects of environmental variables that influence demand such as air quality and environmental concern (Campbell, Cherry et al. 2014). The results were then modeled using binomial logit regression models to estimate the role of different carshare attributes and demographics in the decision to choose carsharing.

2.3.1 Survey design

To investigate the factors influencing the choice to use EV carsharing in Beijing we developed revealed- and stated- preference choice experiments. The first part (Part 1) of the survey is the revealed preference (RP) section where respondents describe real trips and set the baseline for subsequent stated preference (SP) experiments in Parts 2 and 3. In the SP experiments, respondents were provided with an alternative mode, carsharing, with a variety of attributes such as fuel, status indicators, precipitation, temperature, air quality, access time, travel cost, and travel time (Table 2-1). This study hypothesizes that there are preferences for fuel (EV and CV), and a status indicator (Branding or No branding). It also investigates how carshare choice is influenced by environmental factors such as precipitation, temperature, air quality as well as

carsharing attributes including access time, travel cost, and travel time influence. For example, some people may want to use carsharing without anyone knowing (no status) while others prefer EV because of environmental concerns.

Attribute sets are generated based on an orthogonal main-effect design, which is an experimental design used to test the comparative effectiveness of multiple intervention components for experimental attributes (e.g., weather, unit cost, air quality), and the surveyor generates choice scenarios including travel cost and time based on the respondent's answers in the RP section of an existing trip, i.e., peak- and off-peak travel and distance. Table 2-1 summarizes factor levels; various survey forms were developed based on these factors using an orthogonal main-effect design that allows the researcher to test the effectiveness of many interventions with far fewer experimental units. For example, the number of combinations in Table 2-1 is 13,824 and the orthogonal main-effect design suggests 32 units. Two orders (part 2 – part 3 and part 3 – part 2) were developed to prevent answers in Part 3 from being influenced by choice decisions in Part 2; there are 64 different kinds of survey forms. The results revealed no ordering effects.

Table 2-1 Variable levels for stated preference carsharing and environmental attributes

	Factor Level			
	1	2	3	4
Vehicle Type	Battery EV	Gasoline	n/a	n/a
Decals	No	Yes	n/a	n/a
Precipitation	Sunny	Light Rainy	Rainy	n/a
Temperature	0 °C	10 °C	20 °C	30 °C
Air Quality	Good	Moderate	Unhealthy	Hazardous
Access Time	0	5 minutes	10 minutes	15 minutes
Travel Time	No priority lane (Peak/Off-peak)	Priority lane exists (Peak/Off-peak)	n/a	n/a
Cost (part 2)	Structure C	Structure D	Structure E	n/a
Cost (part 3)	12 RMB*/hour (F)	15 RMB/hour (G)	18 RMB/hour (H)	n/a

* RMB is an abbreviation of Renminbi, the official currency of China

The survey form is shown in Figure 2-1. First, respondents are asked to recall trips they made the previous day (Part 1). The respondents report origin, destination, travel mode, departure time, time in/out of vehicle, trip length, trip cost, and number of accompanying travelers. The survey provides an example like 'Distance from the Wudaokou Station to Beijing Language and Culture University is 1.3 Km.' to help the respondents answer about their travel length. Importantly, we do not need to collect any information about unchosen alternative modes.

车共用模式选择研究 (Carsharing mode choice study)

Part-1

Think back to yesterday.

Tell me about all trips you made.
(exclude link trip such as a walking trip from home to bus stop)

Ex> Distance from the Wudaokou station to Beijing Language and Culture University is 1.3 Km.

Part-2

If Carsharing is Launching in Beijing. They are New Energy Vehicles (plug-in electric car). It has same performance as gasoline car. It does not emit pollution from car, but from electric power plant.

The car looks like picture 1.

Suppose that Sunny, 20 °C, air quality is classified as Unhealthy.

You need extra 5 mins for access/egress time for carsharing.

What would you choose?

Part-3

All attributes are same as Part-2.

Now, suppose that you can use the carsharing for your whole daily trips from home.
(Origin – Destinations – Origin, Home-based)

The total travel time is same as Part-2.

The total costs (including fuel and parking) will be _____yuan for your trips (A)

What would you choose?

Origin 1= Home 2=Work 3=School 4=Store 5=Restaurant 6=Entertainment 7=Others	Destination 1= Home 2=Work 3=School 4=Store 5=Restaurant 6=Entertainment 7=Others	Mode 1= bus 2= subway 3= car (drive alone) 4= car (passenger) 5= ebike 6= bike 7= walk 8= taxi 9= motorbike 10= others	*Departure Time*	Travel Time (Out of vehicle/ In-vehicle)	Trip Length *(Km)*	Trip Costs (yuan) Include fare, tolls, parking, and fuel	The number of Travelers with you	Travel time will be A	Travel cost will be A	Mode *1-10 = Same as Part 1* *11 = carsharing*	Mode *1 = Same as Part 1* *2 = carsharing*
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		

清华大学（Tsinghua University)

公用汽车模式选择研究 (Carsharing mode choice study)

Type 23

第一部分

请您回想昨天：.

请您列出您昨天全天的出行过程。
(不包括去公交地铁站的出行，比如从家步行到最近的公交站点)

距离示例：从五道口地铁站到北京语言大学距离为 1.3 公里

第二部分

如果“公用汽车”行动在北京开始启动，使用 新型能源汽车（充电式汽车）。

这辆车看起来像图片 1

假如今天天气是：雨天, 30 °C, 空气质量分类为：良。

您只需要多花 10 分钟使用和归还“公用汽车”车辆。

您的选择是？

第三部分

所有的情况都和第二部分相同。
假设：您现在可以全天使用“公用汽车”车辆（起点-目的地-起点，基家出行）

总出行时间和第二部分中的时间相同

如果您总出行花费（包括燃油和停车）是 _____元 F

您的选择是？

起点 1= 家 2=工作地点 3=学校 4=商场 5=餐厅 6=娱乐场所 7=其他	目的地 1= 家 2=工作地点 3=学校 4=商场 5=餐厅 6=娱乐场所 7=其他	方式 1= 公交 2= 地铁 3=小汽车（自己开车） 4= 小汽车（搭乘） 5= 电动自动车 6= 自行车 7= 步行 8= 出租车 9= 摩托车 10= 其他	出发时间	行程时间 车外 / 车内时间 车外时间=取车+等待时间	出行距离 (公里)	出行花费 (元) 包括车票费、过路费、停车费和燃油费	出行的总人数	出行时间将是 A	出行花费将是 E	出行方式 *1-10 = 和第一部分相同* *11 = “公用汽车”*	出行方式 *1 = 和第一部分相同* *2 =和第二部分相同* *3 = “公用汽车*
				/				分钟	元		
				/				分钟	元		
				/				分钟	元		
				/				分钟	元		
				/				分钟	元		
				/				分钟	元		
				/				分钟	元		

1

Figure 2-1 Survey questions (English and Chinese versions)

Part 2 of the survey is composed of a choice experiment for each RP trip link where the choice set includes the previous mode, a new carsharing mode, and an alternative non-carsharing mode. The environmental attributes (e.g., weather) are explicit and vary in Part 2 and could prompt the respondent to choose another non-carsharing mode. The attributes of the new carsharing mode include performance indicators, a fuel-type indicator (EV or CV), and a status indicator—such as an obvious brand-identity with a large decal so carsharing vehicles cannot be confused with personally owned vehicles. For this part of the survey, respondents were shown an image of the proposed carshare car, a relatively brand- and color-neutral four-door sedan, with or without a decal that clearly says "carshare" (Figure 2-2).

No decals Decals

Figure 2-2 Status indicators

Some attributes of the trip are dynamically assigned based on previous RP trip characteristics, including average speeds (peak- and off-peak) coupled with stated distance. There is some evidence that access to priority lanes can influence demand of alternative fuel technologies (Bolduc, Boucher et al. 2008, Qian and Soopramanien 2011). So, this survey also includes a

varying benefit of priority (e.g., High Occupant Lane or exclusive transit lane access) for the carshare user, represented by reduced travel time. Respondents were instructed to treat all attributes not described in the attribute table as the same across alternatives, though they could carry preconceived ideas about EV performance into the choice experiment.

In Part 3, all attributes are the same as those of Part 2, but respondents are faced with a choice to use carsharing for their round trips (O-D-O trips). The cost is provided, and the respondents can select the original mode, the same mode choice as Part 2, or carsharing. The framework is shown in Figure 2-3.

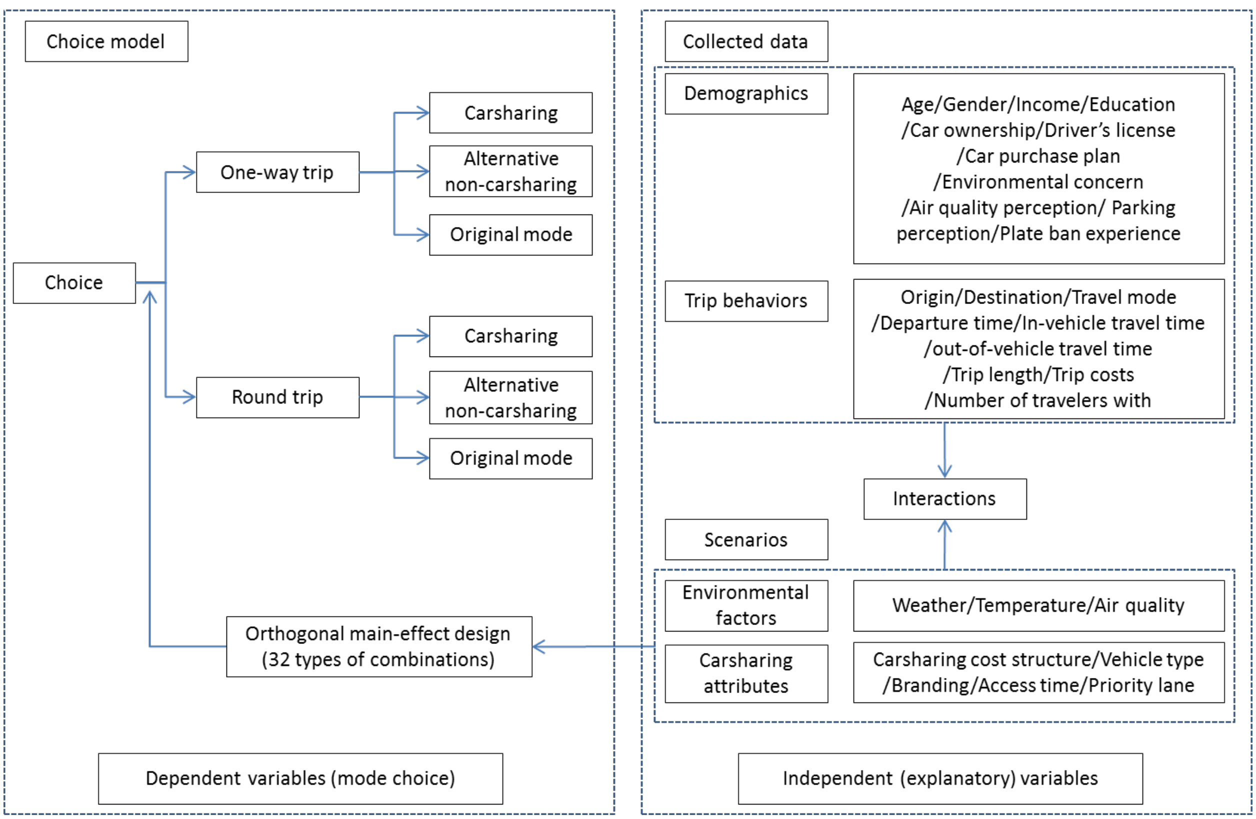


Figure 2-3 Framework of choice model

The design includes three different carshare cost structures as a trip attribute variable for one-way origin-destination trips (O-D trips) to explore how different carsharing cost structures affect responses. Almost all carsharing services are operated by an automated system and may provide different kinds of vehicles. Generally, carsharing fares include fuel and insurance costs. Each respondent is given a random cost structure from orthogonal main-effect design. Figure 2-4 shows the cost structures for three carsharing cost structures and for existing taxi and daily car rental services. The structures are based on the approximate current carsharing and daily rental cost structures (fixed and marginal) based on the travel distance. There are equations for each cost structure on the figure. A taxi fare for daytime (05:00 to 23:00) starts with 13 RMB minimum for 3 Km. After 3 Km, 2.3 RMB is charged for every additional 1 Km. Then after 15 km, 3.45 RMB is charged for additional 1 Km. There are three carshare cost structures for round trip origin-destination(s)-origin trip (O-D-O trip) that are based on hourly charges.

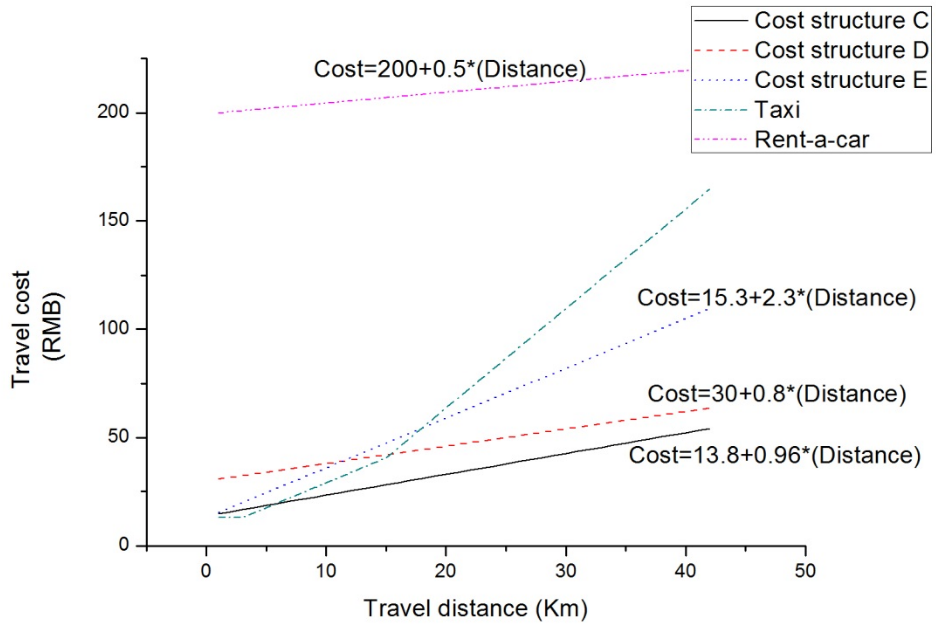


Figure 2-4 Cost structures for one-way (O-D trip)

For the travel time, there are peak times (07:00~09:00 and 17:00~19:00) and non-peak trip times, and each time has two assumptions, using regular lanes and availability of priority lanes (e.g., HOV or exclusive transit lanes). Peak and non-peak times were determined based on respondents' departure time. Table 2-1 shows average speed to calculate travel time when the respondents use carsharing instead of their original modes.

2.3.2 Data collection

In the summer of 2013, a survey was conducted in the seven main districts of Beijing: Xuanwu, Chongwen, Xicheng, Dongcheng, Haidian, Fengtai, and Chaoyang. Xuanwu, Chongwen, Xicheng, and Dongcheng Districts can be categorized as depopulating inner-city districts, which means that for the last 10 years population has decreased. These districts have the oldest population and the average household size remains high and stable (2.8 persons) unlike in other

cities. The remaining three districts are categorized as suburbanizing residential districts where population density has almost doubled in the last 10 years (Tomasz Chaberko 2011). To assess the survey questions and design, a small pilot survey was conducted. The final survey results included 1,010 completed survey forms with 2,023 reported trips (about two trip links per respondent). We expect that the travel diary underreports trip links and tours (Ni, Cherry et al. 2012). The response rate was approximately 43%. The male response rate (46%) was higher than the female response rate (41%). Low quality or incomplete surveys were eliminated.

2.3.3 Choice model

In this paper, we formulate a mixed logit model of the decision to choose carsharing across different carshare attributes and demographics. As a class of discrete choice models, the mixed logit model predicts the dependent variable from several independent variables with linear combination of the predictor variables. Many studies related to vehicle choice model have utilized the mixed logit model. Adoption of electric motorcycles in Vietnam (Jones, Cherry et al. 2013), preference surveys for alternative-fuel vehicles (Brownstone, Bunch et al. 2000), potential customers' choice between gasoline, electric, and hybrid vehicles in California (Hess, Train et al. 2006), and mode choice between monorail, car, and bus in Japan (Shen 2009) are all examples that develop a mode choice model using the mixed logit model.

The model we use here follows Revelt and Train (Revelt and Train 1998). Let us assume that a person confronts a choice among a set of *J* alternatives in time period *T*. The utility that person n obtains from alternative *j* in choice situation *t* is $U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt}$, where x_{njt} is a vector of explanatory variables including carshare attributes and demographics, and ε_{njt} is an iid (independent and identically distributed) extreme value and unobserved random term. β'_n is a coefficient vector which is unobserved for each n and varies in the population with

density $f(\beta_n|\theta^*)$, where θ^* is underlying parameter of the distribution. Person n chooses an alternative *i* in choice situation when the alternative *i* provides higher utility than other alternatives, $U_{nit} > U_{njt} \ \forall i \neq j$.

The probability that person *n* chooses *i* in situation *t* under the conditional on β_n is the standard logit:

$$L_{nit}(\beta_n) = \frac{e^{\beta'_{njt}X_{njt}}}{\sum_j e^{\beta'_n X_{njt}}} \tag{1}$$

If the study assumes that researcher observes β_n, the probability can be simply expressed as a standard logit, but unconditional choice probability is required instead of conditional choice probability because the researcher does not observe β_n. Unconditional probability means the integral of the conditional probability over the density of β_n values, which depends on the parameters of the β'_n distribution:

$$Q_{nit}(\theta^*) = \int L_{nit}(\beta_n) f(\beta_n|\theta^*) d\beta_n \tag{2}$$

Choice probability of mixed logit model is the mixed form of logit model and probability density function, $f(\beta_n|\theta^*)$ and IID issue can be overcome with appropriate $f(\beta_n|\theta^*)$. Let *i(n,t)* denote the alternative that person *n* choses in choice situation *t*. The probability of observing the sequence of choices of person *n* is the product of standard logits:

$$S_n(\beta_n) = \prod_t L_{ni(n,t)t}(\beta_n) \tag{3}$$

The unconditional probability for the sequence of choices from equation (2) and (3) is

$$P_n(\theta^*) = \int S_n(\beta_n)\, f(\beta_n|\theta^*) d\beta_n \tag{4}$$

The log-likelihood function is

$$LL(\theta) = \sum_n ln\, P_n(\theta) \tag{5}$$

and θ must be estimated by maximizing an equation (5) with respect to θ. As a function plays a key role to estimate parameters from a set of statistics, log-likelihood function is approximated by simulation since exact maximum likelihood estimation is not possible due to impossibility of analytical calculation the integral in equation (2). The coefficients of the binomial logit model to estimate carsharing choice are estimated by full information maximum likelihood.

2.4 SURVEY RESULTS

2.4.1 Respondent demographics

Respondent demographics, cross tabulated with mode choice characteristics, are shown in Table 2-2 and Table 2-3. As shown in Table 2-2, respondents who have higher income (more than 8,000 RMB per month) have a different trip mode pattern. As expected, they are more likely to prefer private modes of transportation to public transit.

Table 2-3 shows demographic statistics. The gender distribution among the respondents is slightly more male than female. The gender split in this paper reflects the China National

Population Census 2010. Approximately 45% of respondents have a driver's license, although only 20% of the people in Beijing have one. Around half (49.7%) of the respondents do not own a car.

This survey has three discrete choice outcomes: original mode, switching to carsharing, and switching to an alternative non-carsharing mode. Among total 2,023 trips, 12% of the trips are potential carsharing trips and only 1% of trips switch to an alternative non-carsharing mode. Most respondents (87%) did not shift from their original modes.

Table 2-2 Comparison of trip mode by income levels

	Bus	Subway	Car (Drive alone)	Car (Passenger)	Electric bicycle	Bicycle	Walk	Taxi	Motorbike	Others
Income <8000 RMB	30%	36%	6%	2%	3%	6%	14%	2%	1%	1%
Income >8000 RMB	14%	24%	34%	1%	7%	4%	9%	7%	0	0

Table 2-3 Demographic characteristics of the sample

	Total Sample N=2023 (trips)	Mode choice		
		Carsharing (12 %)	An alternative non-carsharing (1 %)	No change (87%)
Gender				
Male	1046 (52%)	137 (13%)	9 (1%)	900 (86%)
Female	977 (48%)	109 (11%)	14 (1%)	854 (87%)
Driver license				
Yes	916 (45%)	126 (14%)	11 (1%)	779 (85%)
No	1107 (55%)	120 (11%)	12 (1%)	975 (88%)
Age				
Less than 20	203 (10%)	23 (11%)	5 (2%)	175 (86%)
21-25	761 (38%)	57 (7%)	8 (1%)	696 (91%)
26-30	470 (23%)	69 (15%)	8 (2%)	393 (84%)
31-35	232 (11%)	47 (20%)	2 (1%)	183 (79%)
36-40	133 (7%)	22 (17%)	0	111 (83%)
41-45	91 (5%)	7 (8%)	0	84 (92%)
46-50	58 (3%)	11 (19%)	0	47 (81%)
51-55	29 (1%)	6 (21%)	0	23 (79%)
56-60	26 (1%)	0	0	26 (100%)
61-65	14 (1%)	2 (14%)	0	12 (86%)
More than 65	6 (0%)	2 (33%)	0	4 (67%)
Income				
No answer	43 (2%)	6 (14%)	1 (2%)	36 (84%)
2000 RMB or less	426 (24%)	41 (9%)	9 (2%)	426 (90%)
2000-4000 RMB	496 (28%)	71 (12%)	7 (1%)	496 (86%)
4000-6000 RMB	372 (22%)	61 (14%)	3 (1%)	372 (85%)
6000-8000 RMB	204 (12%)	28 (12%)	3 (1%)	204 (87%)
8000-10000 RMB	106 (6%)	18 (15%)	0	106 (85%)
10000-12000 RMB	54 (3%)	8 (13%)	0	54 (87%)
12000 RMB or more	60 (4%)	13 (18%)	0	60 (82%)
Education				
No answer	7 (0%)	0	0	7 (100%)
Grade school or less	136 (7%)	18 (13%)	3(2%)	115 (85%)
High or technical school	461 (23%)	57 (12%)	4 (1%)	400 (87%)
Undergraduate or advanced technical school	1160 (57%)	137 (12%)	11 (1%)	1012 (87%)
Graduate school or more	259 (13%)	34 (13%)	5 (2%)	220 (85%)
Number of cars in household				
0	1005 (49%)	93 (9%)	16 (2%)	896 (89%)
1	801 (40%)	122 (15%)	7 (1%)	672 (84%)
2	160 (8%)	210 (13%)	0	139 (87%)
3 or more	57 (3%)	10 (18%)	0	47 (82%)

2.4.2 Respondent travel behaviors

Table 2-4 reveals that respondents who use a taxi are more likely to switch to carsharing than other modes. Carsharing can be an alternative mode for taxi because of the relatively low carsharing cost structure for specific travel distances, particularly when compared with taxi as shown in Figure 2-3 in the survey. Sheltered (bus, subway, car, taxi) and non-sheltered (e-bike,

bike, walk, motorcycle) modes are broadly classified to highlight environmental exposure and comfort levels relative to weather and pollution. Motorized (bus, subway, car, taxi, motorcycle) and non-motorized (e-bike, bike, walk) modes are classified comfort levels relative to travel distances and weather. Personal (car, e-bike, bike, walk, motorcycle) and Public (bus, subway, taxi) modes are classified to comfort level relative to number or travelers and accessibility.

Table 2-4 Trips mode statistics

	Total Sample N=2023 (trips)	One-way mode choice		
		Carsharing (12%)	An alternative non-carsharing (1%)	No change (87%)
Incumbent Mode				
Bus	569 (28%)	75 (13%)	4 (1%)	490 (86%)
Subway	693 (34%)	73 (11%)	5 (1%)	615 (89%)
Car (Drive alone)	203 (10%)	43 (21%)	1 (0%)	159 (78%)
Car (Passenger)	35 (2%)	2 (6%)	0	33 (94%)
Electric Bicycle	65 (3%)	4 (6%)	0	61 (94%)
Bicycle	110 (5%)	10 (9%)	4 (4%)	96 (87%)
Walk	263 (13%)	12 (5%)	9 (3%)	242 (92%)
Taxi	53 (3%)	23 (43%)	0	30 (57%)
Motorbike	10 (0%)	0	0	10 (100%)
Others	22 (1%)	4 (18%)	0	18 (82%)
Sheltered Mode				
No Shelter	448 (22%)	26 (6%)	13 (3%)	409 (91%)
Sheltered	1575 (78%)	220 (14%)	10 (1%)	1345 (85%)
Motorized Mode				
Non-motorized	373 (18%)	22 (6%)	13 (3 %)	338 (91%)
Motorized	1650 (82%)	224 (14%)	10 (1%)	1416 (85%)
Personal Mode				
Public Mode	1372(68%)	177 (13%)	9 (1%)	1186 (86%)
Personal Mode	651 (32%)	69 (11%)	14 (2%)	568 (87%)

Table 2-5 presents an origin and destination table to assess trip behaviors of respondents. Most trips are categorized as home based work trips. Other popular trip purposes are shopping, school, entertainment, restaurant trips and others.

Table 2-5 O/D table

Origin \ Destination	Home	Work	School	Store	Restaurant	Entertainment	Others	Total
Home	12	499	65	105	23	74	92	870
Work	507	2	11	2	1	0	8	531
School	75	9	31	22	10	5	18	170
Store	105	4	21	0	1	2	8	141
Restaurant	27	1	10	0	0	1	1	40
Entertainment	68	3	6	3	2	1	11	94
Others	101	11	18	6	0	8	33	177
Total	895	529	162	138	37	91	171	2023

2.5 MODEL RESULTS

The survey data was used to build a binomial logit regression because only 1% of respondents chose an alternative non-carsharing mode. This study presumes the reason why the respondents would likely to choose an alternative non-carsharing mode is because experimental attributes including weather, air quality, and temperature may affect the mode switch decision between unsheltered and sheltered non-carsharing modes. The sign of the coefficients indicates the relationships between independent variable and dependent variable, i.e., the dependent variable (probability of choosing carsharing) has positive relationships with the independent variable with (+) coefficient. The *p*-value shows how significant the variables are. Exp (B) is the odds ratio, measuring the impact on the odds of a one-unit increase in only one of the independent variables (Anderson, Sweeney et al. 2011). Multicollinearity was tested through Variance Inflation Factors (VIF), which measure how much the variance of the estimated coefficients are increased over the case of no significant correlation among the variables included in the model.

2.5.1 Demographics

When it comes to choosing carsharing, age and gated apartment residents (weakly significant, *p*-value: 0.076) are positive and significant. Older people are more likely to choose carsharing than younger people. People who live in the gated apartment complex are more likely to choose

carsharing than others. In addition, household car ownership is a significant variable in the decision to switch to carsharing. Households that own cars have a higher probability of using carsharing. This reflects responses indicating that 70% of respondents would still buy a new car even though they can use a carsharing system. Contrary to expectations, carsharing helps more people with cars instead of people who do not own a personal vehicle. This contrasts with recent research that found carsharing contributes to reduced personal car ownership in households (Cervero and Tsai 2004, Shaheen and Martin 2006, Shaheen and Cohen 2007, Martin, Shaheen et al. 2010). Some demographic information including gender, education level, and driver license are not significant in the model.

2.5.2 Trip attributes

If someone is used to paying for a taxi, riding the subway with many people or using sheltered modes of transportation, that person is more likely to consider carsharing. There is more variation in the cost of taxi in the survey than the cost of other modes. While the fare of public transit is fixed and very low with no variation, taxi costs vary dramatically in the model. Positively significant interactions were found between subway users and the number of travelers; taxi users and travel cost; and sheltered modes (bus, subway, car, passenger car, taxi) and unsheltered modes (e-bike, bike, walk, motorcycle). Interactions between other modes and travel cost were not significant. Neither were total travel time (sum of in vehicle time and out of vehicle time), public transit user indicator, peak-time indicator, and single traveler indicators.

Parking conditions perceptions are a significant factor. Respondents are more likely to choose one-way carsharing if they perceive parking conditions are good. Perhaps respondents who identified parking conditions as bad may have already decided to use public transit (Morrall and Bolger 1996). This parallels Birkhardt's 2006 study that indicates one of the main reasons to

choose carsharing is no parking hassles (Burkhardt and Millard-Ball 2006) and parking pressure is one of the factors that make successful carsharing (Hampshire and Gaites 2011, TCRP September 2005). We did not include free or convenient parking as an attribute of carsharing. Thus its role in carsharing decisions will remain a question for future research.

2.5.3 Environmental factors

Since carsharing can be categorized as a sheltered mode, trip purpose could be narrowed by weather conditions. For example, bad weather is not conducive for outside activities. The cold weather indicator in the scenarios (0, 10, 20, and 30°C represent Beijing's four seasons) is a significant factor. People who experience warmer weather (not 0°C) in the scenario are more likely to choose carsharing. Yet the cooler weather (not 30°C) scenario, interaction between rain and out of vehicle time, and interaction between air quality and out of vehicle time do not appear to be significant for carsharing. This contrasts with recent research regarding bicycle travel behaviors that revealed weather factors such as precipitation and temperature significantly impact bicycle travel (Gallop, Tse et al. 2012, Saneinejad, Roorda et al. 2012, Campbell, Cherry et al. 2014). Carsharing is a sheltered mode and shifts toward carsharing could come from other sheltered modes, yielding limited environmental impacts.

2.5.4 Carsharing attributes

Previous research found "acceptable cost" was a reason for choosing to carshare (Burkhardt and Millard-Ball 2006). Carsharing decisions are sensitive to the cost gap (defined as marginal cost of original mode -cost of carshare) between the carsharing rates they will pay and the respondents' original travel costs. Unfortunately other studies have not examined carsharing willingness to pay with realistic carsharing fares. This study investigates how people respond to that cost gap between the original mode and carsharing. People who pay lower travel costs are

less likely to choose carsharing than people who pay more. This may be because public transit fares are relatively cheap in Beijing. The Beijing metro fare is 2 RMB (about $0.30), regardless of travel distance. The bus fare is only 0.4 RMB.

Beyond cost, distance or effort to get to the carsharing vehicle was found to be the least attractive feature of carsharing (Burkhardt and Millard-Ball 2006). But in this study carsharing attributes like fuel type (EV or CV), carshare branding, access time, and priority lane are insignificant. This study presumes the reason why people in Beijing do not consider the access time as a significant variable to choose carsharing is because about 62% of respondents currently take bus or subway that requires access time.

Table 2-6 Binomial regression results (one-way, O-D trip)

Category		*Unit*	*Coeff.*	*Std.err.*	*p-value*	*Exp (B)*
Demographics	Gender (Male)	Binary	.038	.150	.798	1.039
	Age	Age (number)	.015	.007	.040	1.015
	Income	Category (1 to 7)	.029	.050	.563	1.029
	Education (No college education)	Binary	.124	.281	.660	1.132
	Non-gated apartment residents	Binary	-.306	.173	.078	.736
	Non-car owner	Binary	-.438	.163	.007	.645
	No driver's license	Binary	-.027	.167	.874	.973
Trip behaviors	Total travel time	Minutes	.000	.001	.754	1.000
	Subway*number of travelers	Person	.169	.095	.077	1.184
	Taxi*travel costs	RMB	.027	.009	.002	1.027
	Public transit user	Binary	.321	.244	.188	1.379
	Non-sheltered mode user	Binary	-1.082	.315	.001	.339
	Non-peak-time traveler	Binary	-.062	.147	.671	.940
	Non-single traveler	Binary	-.083	.186	.657	.920
	Perceived parking condition	Category (0, bad to 10, good)	.090	.033	.006	1.094
Environmental factors	Rain*out of vehicle time	Minutes	.000	.006	.975	1.000
	Air quality *out of vehicle time	Minutes	.000	.004	.988	1.000
	Not cold weather (Not 0°C)	Binary	.481	.189	.011	1.618
	Not hot weather (Not 30°C)	Binary	.233	.172	.175	1.262
Carsharing attributes	Cost gap (original mode-carsharing)	RMB	.008	.002	.000	1.008
	Access time	Minutes	-.065	.065	.312	.937
	Fuel (EV)	Binary	.056	.143	.694	1.058
	Decal	Binary	.012	.143	.934	1.012
	No priority lane	Binary	.193	.143	.177	1.213
Model statistics						
Observations		2000				
-2 Log Likelihood Final		1377.561				
McFadden pseudo R^2		.105				

The model presented in Table 2-7 is a binary logit regression between carsharing and the previous mode choice for a round trip. Demographic information including gender, income, car ownership, and environmental concerns are likely to be significant factors in O-D-O trip carsharing decisions. Males and car owners as well as people with high environmental concern or higher income levels (over 8,000 RMB per month) are more likely to switch to carsharing from their existing modes.

These results show that the type of trip determines how car ownership impacts mode choice. People who already own cars are more likely to choose carsharing for one-way trips. But people who do not own cars are more likely to use carsharing for round home-based O-D-O trips. This helps explain why 70% of our respondents would still buy a new car even though they can use a carsharing system. Multiple passenger trips appear to be more suitable for carsharing than single passenger trips, particularly round trips. And it is hard to explain why, but people who use the bus are more likely to choose carsharing.

The cost gap is the most significant value for both one-way and round trips. Like one-way carsharing trips, round trips users' demographic information including gender, income and environmental concern are significant. Unlike the one-way trips, the factor related to number of travelers is significant for round trips. This study presumes this is because the fare per person becomes lower.

Table 2-7 Binary logit regression results (origin-based round, O-D-O trip)

Category			*Coeff.*	*Std.err.*	*p-value*	*Exp (B)*
Demographics	Gender (Male)		.395	.165	.017	1.484
	Income (<8,000RMB/month)		-.475	.230	.039	.622
	Car ownership (Ref: Car owner)		.452	.169	.007	1.572
	Environment Concern (0, not at all concerned to 10, very concerned)		.099	.035	.005	1.104
Trip behaviors	Total travel cost	< 0.4 RMB	-1.656	.339	.000	.191
		< 23 RMB	-.939	.306	.002	.391
		23 RMB up				
	Departure time	Morning peak	.682	.467	.144	1.978
		Non-peak	.110	.468	.815	1.116
		Evening peak				
	Group traveler (Ref: Single traveler)		.430	.190	.024	1.537
	Original mode did not involve bus		-.804	.184	.000	.448
Carsharing properties	Fuel (Ref: Gasoline)		-.104	.162	.523	.901
	Decal		.233	.163	.153	1.262
	Access time	0 min	.121	.232	.601	1.128
		5 min	.107	.233	.646	1.113
		10 min	.129	.235	.584	1.138
		15 min				
	Cost gap ((-) means money loss)		.006	.002	.001	1.006
Model statistics						
Observations			1010			
-2 Log Likelihood Final			998.948			
McFadden pseudo R^2			.109			

2.6 CONCLUSION

Beijing is suffering from vehicle traffic congestion and environmental challenges with rapid economic development. The economic activity of Beijing has increased steadily, and population density is high. The Beijing government is making strides to solve these issues by encouraging public transit and alternative fuel vehicle use. In North America and Europe, carsharing plays an important role in reducing congestion and improving air quality. Therefore, carsharing could also be a solution for Beijing's traffic congestion problem. Moreover, despite Beijing's reliance on heavily polluting coal power plants (Ji, Cherry et al. 2011), EVs are seen as a potential solution to improve local air quality (Zheng, Mehndiratta et al. 2012).

The binomial logit regression model revealed several significant factors in carsharing decisions. The most significant factor to carsharing remains the cost gap. Interest in one-way and roundtrip carsharing declined as the cost gap increased. People who already own cars find carsharing useful for one-way trips. This reflects the summary statistics that only 6% of respondents will cancel plans to buy a new car and 25% would postpone those plans. Relatedly, people whose income is more than 8,000 RMB per month are more likely to choose carsharing for roundtrips.

Other factors are also significant. For those who do not own cars (more likely those with lower income), carsharing is more often considered for home-based round trips and the travel tends to be in groups. For people accustomed to traveling in a sheltered mode and under the scenario with harsh air quality and weather conditions are more likely to cause them to choose an alternative transportation mode. Predictably, people with high environmental concern are more interested in carsharing.

Some demographic information including gender, age, gated apartment resident, and driver's license are significant in at least one of the models. Older people are more likely to choose carsharing and gated apartment residents are more interested in the carsharing choice. On the other hand, younger people are more likely to switch their modes to an alternative non-carsharing mode under different environmental conditions, and gender is significant for only the round trip carsharing choice model; males are more likely to choose carsharing for home-based round-trips. The finding about age in this study contrasts the carsharing survey analysis in Shanghai that concluded younger people are more interested in carsharing than older people (Wang, Martin et al. 2012).

Some interactions proved to be significant. People whose original travel mode is the subway, traveling with many people are more interested in carsharing than subway travelers with few people. This indicates that not only comfort, but also cost plays a role in this decision. The carsharing fare per person becomes lower with more people while the comfort level remains similar. The interaction with a taxi user and cost is also significant. Carsharing can be an alternative mode for taxi users because it has a competitive fare.

People who perceived good parking conditions are more likely to choose carsharing because they may have experienced less difficulty finding parking spots. This shows similarity to previous studies about relationships between carsharing and parking issues (Burkhardt and Millard-Ball 2006, Hampshire and Gaites 2011). Non-cold weather (10, 20, 30°C) conditions are more supportive of carsharing low (winter) temperature (0°C). The hot weather indicator, interaction between rain and out of vehicle time, and interaction of air quality and out of vehicle time are insignificant for the one-way carsharing choice model. But the interaction between air quality and out of vehicle time is significant for those switching mode to an alternative non-carsharing mode under various environmental conditions.

Contrary to expectation, carsharing attributes including fuel type, branding, access time, and potential priority lane benefit are not significant in the carsharing models. The key finding here is that EVs by themselves are not more attractive that CVs. Also, to the extent that a large decal advertising that you are using a carshare vehicle is any indicator of status (positive or negative), had no influence on choice. Other trip attributes such as total travel time, public transit indicator, peak-hour indicator, and single traveler indicator are also insignificant.

Success of any carsharing system depends on competitive fares. The cost must be different for different services (one-way and round trip); significant factors affecting carsharing willingness to pay vary for each kind of service. This paper is the first to analyze a carsharing choice model with the cost gap between original cost and three different potential carsharing costs, a comfort index, group travel behavior, levels of environmental concern, and different environmental factors such as weather, temperature, air quality, along with carsharing attributes including vehicle type (EV and CV), branding, and access time.

This research can help urban areas determine carsharing feasibility, prepare carsharing policies and identify potential target markets. Both city officials and entrepreneurs can use it. For city officials, it predicts that positive effects such as better air quality and less congestion could be achieved in Beijing if a carsharing system were adopted. For potential carsharing system owners, it shows that carsharing should be targeted to private car drivers and taxi users rather than public transportation users. And locations should be structured differently to accommodate a variety of preferences determined by where all requirements such as demands, accessibility, and distance between locations are met and conditions that were suggested in this paper including demographic composition and cost structure for carsharing in Beijing. Equipped with this research, they would increase their likelihood of building a successful carsharing system.

3 CARSHARING FLEET OPTIMIZATION THROUGH MODE CHOICE MODEL: A CASE STUDY OF BEIJING, CHINA

ABSTRACT

Carsharing helps mitigate transportation congestion, parking, environmental, and social transportation challenges in cities. Besides providing vehicle access to lower income households, it lowers emissions and reduces vehicle miles traveled (VMT) as well as the number of vehicles registered. Despite these benefits, the carsharing market has been slow to develop in China. This paper explores potential carsharing demand, fleet size, and economic performance in Beijing. To determine these, a carsharing mode split is estimated by a utilization function derived from a binomial logit regression. Adequate fleet size is estimated through a simulation that includes factors such as vehicle types (electric or gasoline vehicle), charger types for electric vehicles (level 2 or level 3 chargers) that influence charging time, arrival rates, travel distance, and travel time based on the time intervals (peak or non-peak hours). In addition, this study estimates the payback period to recover sunk costs. Results indicate that the carsharing mode split ranges from 9% - 32% and an electric vehicle fleet with level 2 chargers is more appropriate for carsharing in Beijing.

3.1 INTRODUCTION

Carsharing has emerged as a transportation mode to solve urban cities' problems with congestion, parking and pollution. It also provides affordable car access for lower income populations. People can rent cars by the hour and return them to a station near their destination. Carsharing services are becoming widespread in North America and Europe but rapidly developing Asian countries have been slow to adopt (Barth, Shaheen et al. 2006). The target area of this study, Beijing, has had small-scale carsharing services with relatively low levels of success.

This paper focuses on three main issues in Beijing, (1) the potential carsharing demand, (2) the optimized carsharing fleet size, and (3) the optimal carsharing system vehicle type--conventional vehicles (CVs) or electric vehicles (EVs). It begins by asking who is more likely to use carsharing in Beijing and continues by determining a carsharing system's scale and feasibility. This is based on estimating the potential demand (mode split). After that, this study explores how to optimize the fleet's vehicles in terms of size and vehicle type. When compared with CVs, EVs can have a lower environmental impact, lower maintenance and lower fuel costs. Since EVs and CVs vary on several points including purchase price, maintenance costs, fuel efficiency, fuel price, and the range between refueling, the resultant system design and economics differ. One important consideration is that EVs' trips are limited to about 160 km (100 miles). EVs also have a higher initial purchase price because of high battery costs. And the higher infrastructure costs vary based on the charger speed level (1, 2 or 3). This sunk cost is one of the primary barriers to developing robust EV carsharing systems.

To estimate the carsharing fleet size that will satisfy the estimated carsharing demand in Beijing, a simulation is used. Charging time is the most significant factor because an EV with a level 2 charger needs to be charged for 3 hours every 160 km, while an EV with a level 3 charger only

requires 20-30 minutes of charging every 160 km. And CVs need about 5 minutes for refueling every 300 km. That recharging time must be factored in with customer demand. The simulation estimates the number of vehicles required in the fleet based on customer arrival time, travel distance, travel time, and charging time for each vehicle type.

Balancing all these considerations, this paper analyzes feasibility, accesses market potential, and forecasts demand for carsharing utilizing revealed- and stated-preference experiments administered during the summer of 2013. The 1,010 completed surveys were conducted across 7 districts and included 2,023 trips. The probabilistic choice model forecasts the demand of a new transportation mode with disaggregate data that can be applied to the urban area to represent overall market share with EVs. The paper also optimizes fleet size and compositions to maximize economic performance.

3.2 BACKGROUND

3.2.1 Carsharing and EVs

By reducing the number of vehicle registered and vehicle mile travel (VMT), carsharing can alleviate transportation and environmental issues (Olsen 2006). This finding is replicated in many North American and European carsharing systems (Tuan Seik 2000, Lane 2005, Olsen 2006, Creutzig and He 2009, TCRP September 2005). Integrating EVs into carsharing systems' could create greater benefits. EVs could further improve carsharing systems' environmental performance while carsharing could help overcome some of the barriers to EV use.

EVs, defined here, run solely on electric power stored in batteries that are recharged from the electrical grid. With a reliance on clean fuel, EVs typically have no tailpipe emissions and many attractive features including decreased greenhouse gas emissions, reduced dependence on

imported petroleum, fewer noise pollutants and potentially a lower cost alternative to gasoline (Funk and Rabl 1999, Taylor, Maitra et al. 2009).

Carsharing fleets with EVs were first introduced in the Bay Area Rapid Transit (BART) station car demonstration program in the San Francisco area that operated nearly 40 EVs in November 1995 (Nerenberg, Bernard III et al. 1999). Another early implementation was French “Praxitele” program in October 1997 with 50 Renault EVs (Shaheen, Sperling et al. 1998). More recently, Austria, Denmark, Finland, France, Japan, Korea, Norway, Portugal, Switzerland, the UK, and other cities in the U.S. use EVs in their carsharing fleets (Shaheen and Cohen 2012, 2013). Most programs have struggled with high vehicle purchase price and infrastructure costs (Shaheen, Sperling et al. 1998). Along with EV purchase prices that are higher than CV purchase prices, EVs require charging infrastructure costs (e.g., Level 2 charger costs about $1,800 (Kevin Morrow 2008)) that are unnecessary for CVs.

To help carsharing system implementation, many studies have used computer simulations. Previous research has explored the effective number of carsharing vehicles to minimize the number of relocations (Barth and Todd 1999); the decision making to own or share a vehicle based on economic performance (Schuster, Byrne et al. 2005); the optimal ratio of vehicles to users to keep the distribution balance between parked vehicles among stations for one-way carsharing (Uesugi, Mukai et al. 2007); the estimated carsharing demand with a utility function(Ciari, Schüssler et al. 2010); and how growth strategies can be impacted by the number and capacities of carsharing stations (Fassi, Awasthi et al. 2012). Even with all this simulation research, there is little research examining how many vehicles are required to satisfy demands with different fleet types: an EV fleet with level 2 chargers, an EV fleet with level 3 chargers, and a CV fleet. To efficiently integrate EVs in a carsharing fleet, initial vehicle and infrastructure

costs, driving range limitations, and long refueling time must be considered. These constraints are coupled with stochastic demand requirements. That complexity motivates the approach used here to study EV carsharing feasibility in Beijing, China.

3.2.2 Probabilistic choice model

Choice models are useful to forecast transportation mode choices with unprecedented, emerging transportation modes. These models rely on disaggregate data from individuals or households. Probabilistic choice models assume that each individual maximizes individual utility by choosing the best option in a choice set (e.g., alternative modes of transportation). The utility function for each mode can include mode-specific attributes as well as demographic attributes. The assumption for the random components of the utilities among the different alternatives is independent and identically distributed (IID). That results in the logit regression model (Johnson and Kotz 1970, McFadden 1973).

The probabilistic choice model is described by the following equations. Assume that C_n is the set of available transportation modes that the individual *n* can choose and U_{jn} is the utility that the individual *n* utilizes when the one choose *j* mode. The equation (1) shows the condition that the individual *n* chooses transportation mode *i*.

$$U_{in} > U_{jn}, i \neq j, \qquad j \in C_n \tag{1}$$

The probability that the individual *n* chooses transportation mode *i*, P_{in} can be expressed as the probability that the utility of transportation mode *i* for individual *n* exceeding the other modes in the choice set (Equation 2).

$$P_{in} = Prob\left(U_{in} > U_{jn}\,; i \neq j, j \in C_n\right) \tag{2}$$

$$= Prob\left(V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}\,; i \neq j, j \in C_n\right)$$

$$, 0 \leq P_{in} \leq 1, \sum_{i \in C_n} P_{in} = 1$$

The logit model assumes the probabilistic utility follows a weibull distribution. The choice probabilities that the individual *n* chooses transportation mode *i* is,

$$P_n(i) = Prob\left(U_{in} \geq U_{jn}, \forall j \in C_n\right) = \frac{e^{V_{in}}}{\sum_{j=1}^{J} e^{V_{jn}}} \tag{3}$$

Maximum likelihood estimation can estimate parameters (*β*) of the utility functions (*V*) resulting in the linear-in-parameters logit with for the choice parameters is in Equation (4)

$$P_n(i) = \frac{e^{\beta' x_{in}}}{\sum_{j \in C_n} e^{\beta' x_{jn}}} \tag{4}$$

3.2.3 New transportation mode choice

Revealed preference (RP) choice modeling is a methodology for comparing how policies influence consumer behavior. RP methods rely on observed behavior of existing systems. For new transportation modes, a stated preference (SP) method asks about realistic but hypothetical situations to analyze feasibility and forecast demand. SP analysis is popular among researchers estimating transportation mode choice decisions, particularly when considering new technologies. The combined estimation of RP/SP data can be more effective to forecast travel demand for new modes or service characteristics (Dissanayake and Morikawa 2010).

This paper develops a carsharing potential demand forecasting model through a binomial logistic regression model that combines RP/SP data to predict the mode split created by the introduction of carsharing in Beijing, China. Based on the model, different scenarios with several explanatory variables are considered to determine the carsharing mode split (%). This rate is used to estimate fleet size and displaced modes as well as analyzes cost effectiveness.

3.3 EXPERIMENT DESIGN AND DESCRIPTION

A pen and paper survey was administered over the summer of 2013 with a response rate of 43% (46% male, 41% female). Respondents were from one of seven districts in Beijing, China. Four (Xuanwu, Chongwen, Xicheng, and Dongcheng) are categorized as depopulating inner-city districts while three (Haidian, Fengtai, and Chaoyang Districts) are considered residential suburban districts. The geography is shown in Figure 3-1.

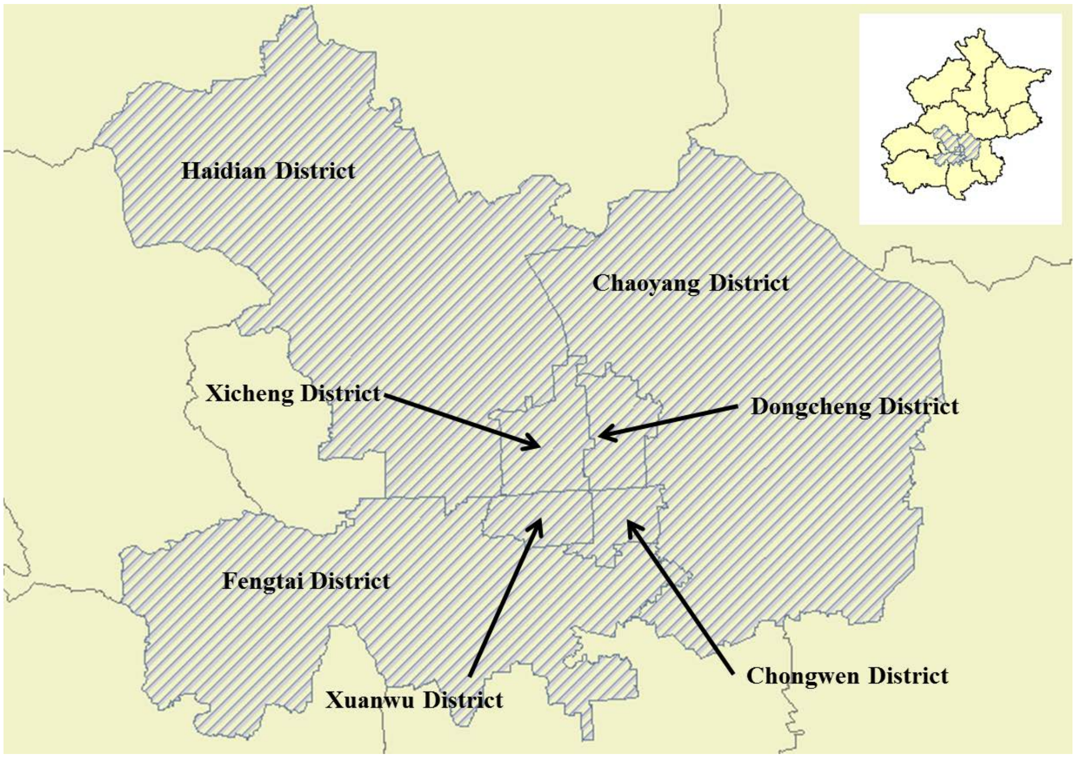


Figure 3-1 Survey locations (7 districts)

The study relies on a pen-and-paper survey that allows a pivoting design to merge revealed preference (RP) and stated preference (SP) components due to tight time and budget constraints (Campbell, Cherry et al. 2014). Part 1 of survey is the revealed preference (RP) section where respondents describe real trips and set the baseline for subsequent stated preference (SP) experiments in Part 2 and 3. Parts 2 and 3 provide experimental attributes of hypothetical carshare modes and then present a choice task considering either one-way trips or round-trips using the previous mode in Part 1 (with experimental environmental attributes) and two types of car sharing (in separate choice tasks). Attribute set are generated based on orthogonal main-effect design, which is an experimental design used to test the comparative effectiveness of multiple intervention components for experimental attributes and the surveyor generates choice scenarios including travel cost and time based on the respondent's answers in the RP section of

an existing trip, i.e., peak- and off-peak travel and distance. Two orders (part 2 – part 3 and part 3 – part 2) were developed to prevent answers in Part 3 from being influenced by choice decisions in Part 2; there are 64 different kinds of survey forms. The results revealed no ordering effects. Factor levels are presented in Table 3-1.

Table 3-1 Factor levels

	Factor Level			
	1	2	3	4
Vehicle Type	Battery EV	CV	n/a	n/a
Decals	No	Yes	n/a	n/a
Precipitation	Sunny	Light Rainy	Rainy	n/a
Temperature	0 °C	10 °C	20 °C	30 °C
Air Quality	Good	Moderate	Unhealthy	Hazardous
Access Time	0	5 minutes	10 minutes	15 minutes
Travel Time	No priority lane (Peak/Off-peak)	Priority lane exists (Peak/Off-peak)	n/a	n/a
Carsharing cost (one-way)	Structure C	Structure D	Structure E	n/a
Carsharing cost (round trip)	12 RMB/hour (F)	15 RMB/hour (G)	18 RMB/hour (H)	n/a

To understand the relationship between mode choice and variables, the survey asks about demographic and perception information such as age, gender, income, level of education, number of cars in household, driver license, car purchase plan, environmental concerns, air quality, parking perceptions, and license plate ban experience. This study hypothesizes that preferences differ with vehicle types (EV and CV), branding (decals), weather, temperature, air quality, access time, priority lane, and cost structures. Carsharing costs for three fleet structures are shown in Figure 3-2.

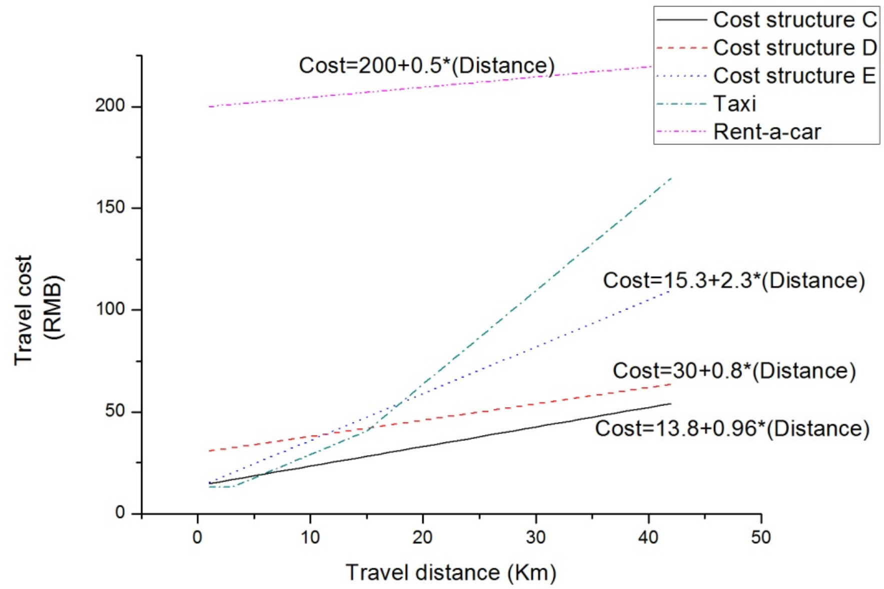


Figure 3-2 Cost structures

The validity of the independence of irrelevant alternatives (IIA) assumption for the logit model is diagnosed by statistical test (McFadden, Train et al. 1977) and this study checks for IIA with the Hausman-McFadden test in SPSS software. For the model, the IIA assumption is supported with the significant level below 0.01. Along with the IIA test, multicollinearity between variables was tested through variance inflation factors (VIF).

3.4 SURVEY DATA ANALYSIS

With a well-developed network and low fares, subway and bus are the major transportation modes in Beijing. People who rely on public transit pay less than car owners or taxi users. As shown in in Table 3-2, they are less likely to use carsharing than respondents who already use more expensive modes like cars or taxis. This implies that a smaller cost gap between the original mode and carsharing fares attracts more people to switch to carsharing.

Table 3-2 shows people who use zero-cost, non-motorized, unsheltered modes such as walking and bicycling often switch to an alternative non-carsharing mode. This study presumes that they are more likely to switch to sheltered modes under harsh conditions, such as bad air quality, temperature extremes, or precipitation.

Table 3-2 Trip mode statistics

	Total Sample N=2023 (trips)	One-way mode choice		
		Carsharing (12.2%)	An alternative non-carsharing mode (1.1%)	No change (86.7%)
Mode				
Bus	569 (28%)	75 (13%)	4 (1%)	490 (86%)
Subway	693 (34%)	73 (11%)	5 (1%)	615 (89%)
Car (Drive alone)	203 (10%)	43 (21%)	1 (1%)	159 (78%)
Car (Passenger)	35 (2%)	2 (6%)	0	33 (94%)
Electric Bicycle	65 (3%)	4 (6%)	0	61 (94%)
Bicycle	110 (5%)	10 (9%)	4 (4%)	96 (87%)
Walk	263 (13%)	12 (5%)	9 (3%)	242 (92%)
Taxi	53 (3%)	23 (43%)	0	30 (57%)
Motorbike	10 (1%)	0	0	10 (100%)
Others	22 (1%)	4 (18%)	0	18 (82%)

3.5 RESULTS AND DISCUSSION

3.5.1 Model estimation

To estimate carshare fleet size, the total market share must be estimated under realistic demand scenarios, controlling for factors that could influence shifts between modes. Table 3-3 shows the explanatory variables.

Table 3-3 Descriptions of explanatory variables

Variable	Description
No car ownership	The rate of households that own no car
Non-private sheltered mode users	The rate of non-private sheltered modes (private sheltered modes include car users (drive and passenger)
Non-public transit users	The rate of non-public transit users (car drive, car passenger, e-bike, bike, walk, taxi, motorcycle, and others)
Subway * Cost gap	Interaction between subway users and cost gap (subway fare – carsharing fare)
Subway * Number of travelers	Interaction between subway users and number of travelers
Car * Cost gap	Interaction between car users and cost gap (car costs (4 RMB/Km) – carsharing fare)
Taxi * Travel distance	Interaction between taxi users and travel distance

In Table 3-4 the explanatory variables are given realistic values. Beijing statistics are used to estimate the cost gap for the interaction between car and cost gap and distance for the interaction between taxi and travel distance. The values collected in the survey are used to estimate the interaction between the subway and number of travelers.

In the chapter 2, the model describes individual mode choice model with collected survey data. On the other hand, the model estimates carsharing mode split in the macroscopic view of Beijing and requires only open-source Beijing statistics data in this chapter. The model reveals a utilization function to estimate the carsharing mode split with a binomial logit model. Survey data evaluates how well the estimation model predicts the carsharing mode split share. The signs of coefficients show the relationship between independent and dependent variables, i.e. positive coefficient indicated positive relationships between the two variables. *P*-value explains how the model fits well and odds ratio, Exp (B) explains the impact on the odds of a one-unit increase in only one of the independent variables (Anderson, Sweeney et al. 2011).

Table 3-4 Carsharing probability estimations of the logit model

Variable	Units	Estimate	Robust standard error	Exp (B)	p-value
No car ownership	%	-.407	.151	.666	.007
Non-private sheltered mode users	%	-1.167	.274	.311	.000
Non-public transit users	%	-.924	.230	.397	.000
Subway * Cost gap	RMB	.018	.005	1.019	.000
Subway * Number of travelers	Person(s)	.306	.099	1.358	.002
Car * Cost gap	RMB	.010	.003	1.010	.006
Taxi * Travel distance	km	.059	.017	1.061	.001

Model statistics	
Observations	2023
-2 Log Likelihood	565.533
McFadden pseudo R^2	.054

The estimation model with survey data shows a mode split of 13%, which is close to the survey's carsharing mode split of 12%. Those more likely to shift to carsharing include subway or car users who have a low cost gap between their previous mode and carsharing; subway users who travel with more people; and taxi users with long travel distances. The taxi users may shift because of carsharing's competitive cost structure. The subway users who travel with more people may shift for convenience and privacy benefits. In groups, the carsharing fare per person becomes lower. Unlike what was expected, carsharing will attract more people who already own a household car.

3.5.2 Potential demands

Potential demands for carsharing are estimated using 324 different scenarios which include travel distance, number of travelers, rate of public transit users, rate of private sheltered mode users, and rate of households without cars. That information is based on Beijing statistics and survey data with 3 different kinds of cost structures as shown in Figure 3-2. Distance (average travel distance in Beijing is 7.6 Km) ranges from 5 Km to 10 Km (with a 2.5 Km increment); the number of travelers ranges from 1 to 1.4 (with a 0.2 person increment); rate of public transit

users ranges from 45% to 65% (with a 10% increment); rate of private sheltered mode users ranges from 30% to 40% (with a 5% increment); and the rate of household that own no car ranges from 50% to 80% (with a 10% increment).

Carsharing mode split ranges from 9% to 32%. Table 3-5 shows some of the scenarios with the average mode split under different cost structures. When the results are compared with the results of Pittsburgh's case study (the carsharing market has 0.06 to 25% adoption rate of car owners) (Hampshire and Gaites 2011), this result would be reasonable because the cities have different orientations. Beijing is transit-oriented and Pittsburgh is much more personal car-oriented.

Table 3-5 Carsharing mode splits under scenarios

Distance (km)	Number of travelers	Ratio of public transit users	Ratio of private sheltered modes	Ratio of household own car(s)	Carsharing mode split under cost structures		
					C	D	E
5 7.5 10	1 1.2 1.4	65% 55% 45%	40% 35% 30%	50% 40% 30% 20%	Avg: 0.22 Min: 0.14 Max: 0.32	Avg: 0.15 Min: 0.09 Max: 0.23	Avg: 0.19 Min: 0.12 Max: 0.28

3.5.3 Carsharing simulation

The Monte Carlo (using Python 2.7.6 software) was used to find optimized fleet sizes for different vehicles: CVs, EVs with level 2 chargers, and EVs with level 3 chargers. It was based on randomly distributed departure times and travel distances, travel times for peak and off-peak hours, charging profiles, the number of stations, and station operation hours. Because the simulation revealed that no trips are longer than 160 km, EV single-trip range is less important.

Beyond lower initial costs, one of CVs greatest advantages is extended trips (up to 300 km) before needing to be refueled.

3.5.3.1 Methods

Carsharing systems will provide parking spots and decrease the need for large parking lots. This helps people easily access their destinations and saves the money required to secure and maintain large parking sites. As a city with 6,487 sq. miles or 16,801 sq. km., Beijing is divided into 200 zones (clusters of parking spots) for this study. Within a zone which is similar size as Xicheng District, the simulation focuses on demand variables including trip generation, travel distance (km), travel time (minutes based on peak and off-peak hour average travel speed), and recharging time for EVs (considered level 2 and level 3 chargers).

There are three EV chargers types: level 1, level 2, and level 3. A level 1 charger is a home-charging system with a maximum 2.4 kW; it requires at least 10 hours of charging to go from empty to full. A level 2 charger is a fast AC charging system with either 7 kW (32A single phase) or 21 kW (three-phase); it requires only 3 of hours charging to go from empty to full. A level 3 charger is a fast DC charging system that uses a maximum of 50 kW; it only needs 20 minutes to go from empty to 80% full. Unlike AC charging, DC charging is usually measured up to 80% since the last 20% recharges at a much slower rate (Braunl 2014). A level 1 charger is not appropriate for commercial use, thus this study does not consider them.

3.5.3.2 Trip generation module

This study assumes that an arrival rate follows the Poisson distribution (Ji, Cherry et al. 2013) and a travel distance follows the gamma distribution with the smallest Akaike Information Criterion (AIC), which is a measure of the relative goodness of a statistics model's fit. Even if the carsharing has a 24/7 service system, real trips will occur at some specific time intervals.

This study assumes that trip departures occur between 07:00 am to 10:00 pm and trips will continue until the last trips are finished. All these assumptions and variable distributions are shown in Table 3-6.

Table 3-6 Trip generation assumptions and variable distributions

Variables	Generation	Units
Departure time	Poisson (λ)	trip/day
Travel distance	Gamma (α,δ)	mile
Travel time	Peak hour: 20 km/h Off-peak hour: 30 km/h	minute
Recharging profile	Level 2 charger: 3 hours to fully charged Level 3 charger: 20 minute to fully charged	minute

3.5.3.3 Processing events

Since carsharing is not only for round trips, the simulation was also performed for one-way trips. For example, a vehicle starts from station A and travels to Station F randomly. In addition, this study requires that all cars are fully charged before each trip because charging infrastructure is difficult to access during trips and users should not consider range when determining carshare use. This indicates that vehicles will be recharged after they are checked in so they will be ready for the next customer. The recharging time depends on the previous travel lengths and the EV charger profile. Figure 3-3 shows a flow chart of this process in the simulation.

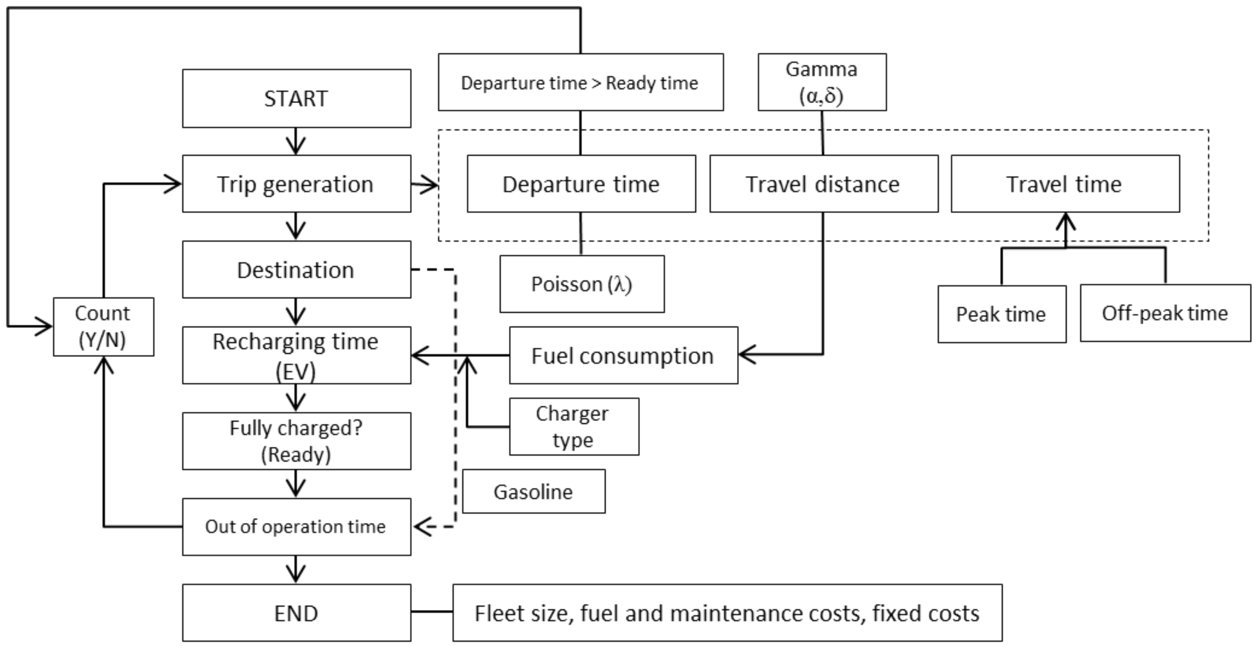


Figure 3-3 Flow chart of simulation process

Fleet size was simulated and the result is shown in Figure 3-4. As shown in the figure, EV fleets with level 2 chargers need significantly larger fleets because every 160 km traveled requires 3 hours to move from an empty to full charge. Since the fleet with level 3 chargers needs only 20 minutes for recharging every 160 km, its size is not so different from the CV fleet. It also is clear that the larger carsharing mode split requires bigger fleets.

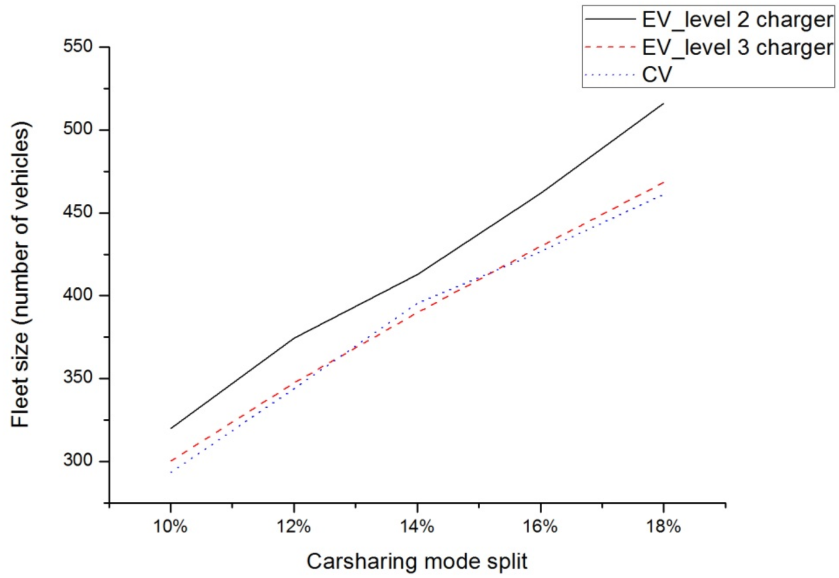


Figure 3-4 Fleet sizes under different carsharing mode splits

Table 3-7 shows annual mileage for each vehicle type. The mileage is more than private cars but less or similar when compared with commercial vehicles such as a taxi. It also shows that CVs require more individual vehicle mileage to satisfy total demands because a gasoline vehicle fleet has a smaller fleet size and shorter fueling time.

Table 3-7 Vehicle mileage

	EV with level 2 charger	EV with level 3 charger	CV
Daily mileage (km)	68	75	83
Yearly mileage (km)	24,866	27,291	30,289

3.5.4 Economic analysis

Carsharing is a business with large sunk costs and a high entry barrier. For example, Zipcar opening costs were $137 million in 2009; 68% of those expenses were fleet operations such as operating vehicle costs (lease, depreciation, parking, fuel, insurance, resale value, accident, repair and maintenance) and employee-related costs (Hampshire and Gaites 2011). Indeed, from the consumer perspective, one of the advantages of carsharing is the normalizing of sunk costs over a vehicle's life. To include charging infrastructure, initial capital requirements increase. And EVs are more expensive than their equivalent CVs. Prices vary among charging infrastructure. To estimate total costs and potential profits, this study uses average prices: $1,800 for a level 2 charger and $18,000 for a level 3 charger. (Kevin Morrow 2008). This study also considers vehicle depreciation rates by vehicle types, as shown in Figure 3-5 (KBB.com Web 2014). Because EVs have recently been introduced to the market, the EV depreciation rate is assumed to be the same as the depreciation rate of a hybrid vehicle.

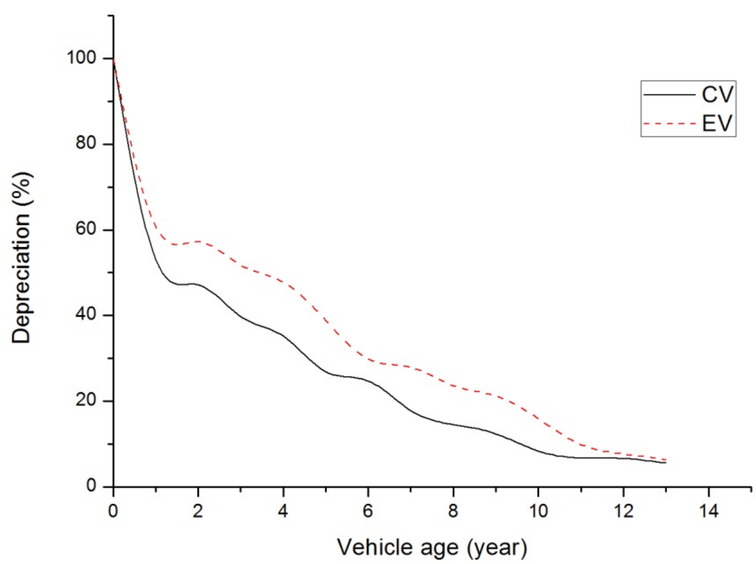


Figure 3-5 Depreciation rate by vehicle type

The assumed information is shown in Table 3-8. The vehicle prices use the Hyundai Elantra and E150EV model because the Elantra models have been used as taxis in Beijing and the information of E150EV model is well described in previous research. The per-kilometer fuel cost of EVs is only one fifth that of a CV, but the purchase price is 9% more (Hao, Wang et al. 2013).

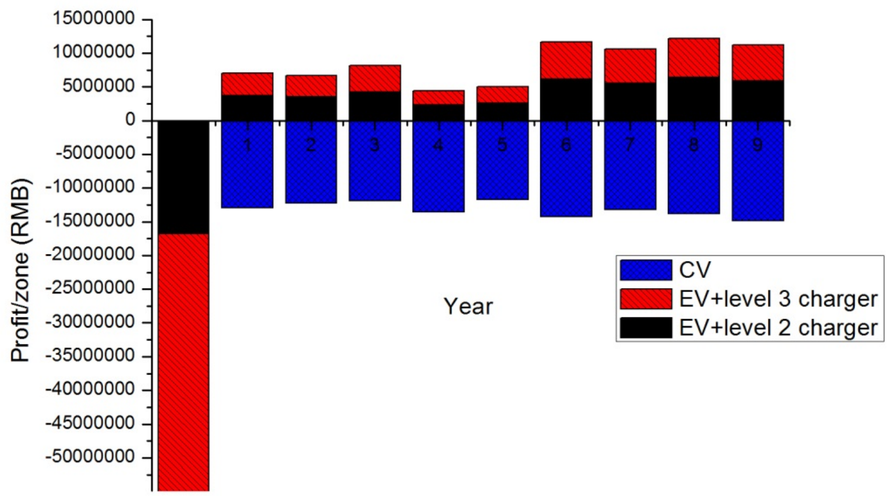
Table 3-8 Assumptions in model

CV	Price	109,800 RMB*
	Monthly payment	2,425 RMB (2.9 % for 4 years)
	Maintenance costs	1 RMB/Km**
	Fuel economy	7.60 L/100Km
	Fuel price	7.75 yuan/L***
	Depreciation cost	Follows gasoline vehicle depreciation rate in Figure 3-6
EV	Price	120,000 RMB including government subsidy
	Monthly payment	2,650 RMB (2.9 % for 4 years)
	Maintenance costs	12 RMB/100Km, 0.12 RMB/Km
	Fuel cost	1/5 of gasoline vehicle (0.81 RMB/kWh)
	Depreciation cost	Follows hybrid vehicle depreciation rate in Figure 3-6
Carsharing mode split		13% from the mode split estimation model with survey statistics
Arrival time		Monte Carlo simulation (Poisson distribution)
Travel distance per trip		Monte Carlo simulation (Gamma distribution)
Revenue		C, D, E cost structures in the survey

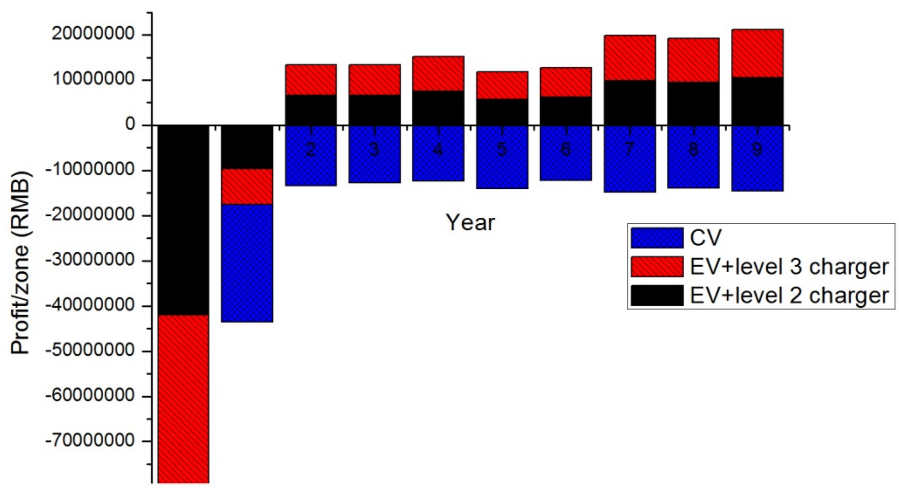
* Hyundai Elantra Model (1.6 GLS Automatic), same model as taxi in Beijing
** Beijing's Goal: 50,000 EVs by 2015, Environmental News Service, May 24, 2013
*** In Beijing as of July 22, 2013

The simulation was performed using the estimated carsharing mode split from the developed model with survey statistics, 13%. In addition, since the survey results show that most trips will occur between 7 am and 10 pm, the simulation only generates trips during that time period. This research assumes that CVs do not need a long time gap between two trips while EVs will need to recharge their batteries at the station between trips. Three different scenarios are used based on the time gap between trips.

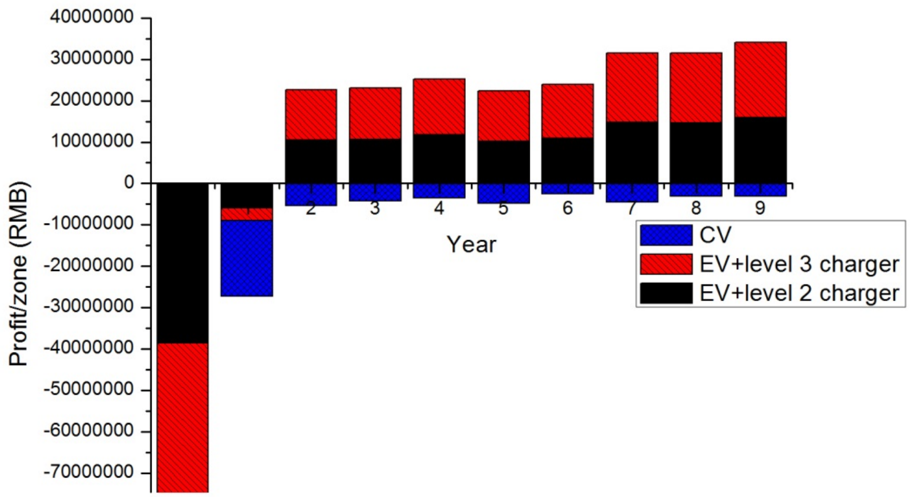
Figure 3-6 illustrates yearly zone profit based on the combinations of vehicle types and cost structures, C (a), D (b), and E (c). CV fleets cannot make a profit under any cost structures because of high gasoline prices and maintenance costs. This may be the reason why carsharing is not active in Beijing.



(a) Profit by year and fleet type under C cost structure



(b) Profit by year and fleet type under D cost structure



(c) Profit by year and fleet type under E cost structure

Figure 3-6 Profit by year and fleet type under 3 different cost structures

Since an EV fleet requires a substantial charging infrastructure, it is necessary to see the break-even point where an EV fleet recovers that initial investment and makes more profits than a CV fleet. This is not difficult since high fuel and maintenance costs ensure that a CV fleet does not make any profit. As shown in Figure 3-7, the fleets with EVs and level 2 chargers under cost structure C and E recover the sunk cost sooner than the other scenarios (in approximately 5 years). This means that to maximize profits over 5 years in Beijing an EV fleet with a level 2 charging infrastructure is more appropriate than a level 3 charging infrastructure.

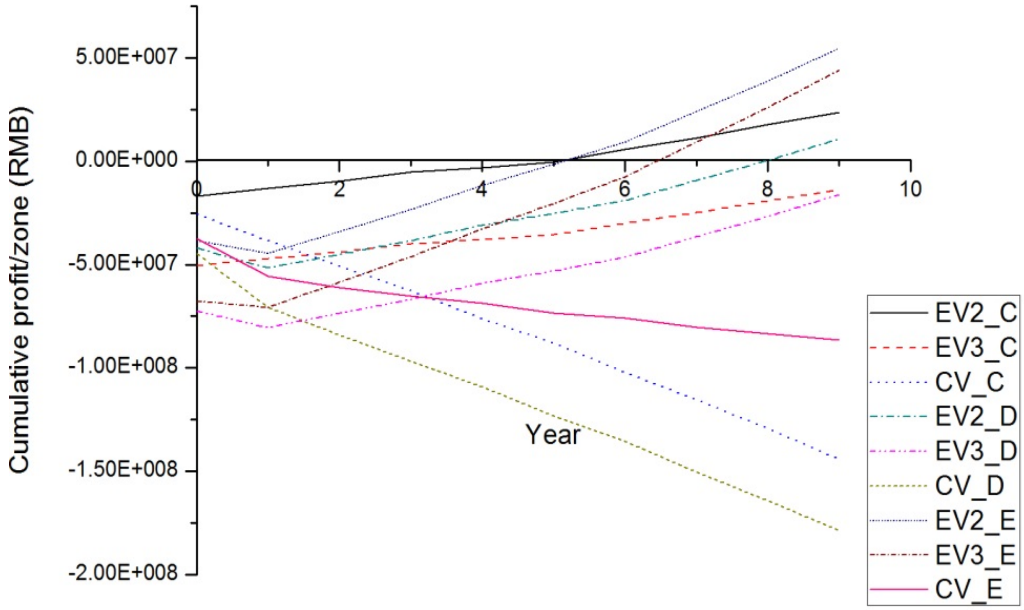


Figure 3-7 Cumulative profit and payback period by fleet type

3.5.5. Sensitivity analysis

Figure 3-7 shows total fleet profit estimates within a zone (13% carsharing mode split) and the fleet size that meets carsharing demand in the zone requires at least 5 years to recover the sunk costs and makes profit. A sensitivity analysis for fleet size is performed to see the cost effectiveness of a smaller fleet. The result shows cumulative profits and payback periods for half- and quarter-sized fleet are same as those of full-sized fleet. Since total costs depend on the number of vehicles, carsharing costs scale proportionally; total costs increase as the fleet size increases. It does not show economy of scale clearly. Regardless of the fleet sizes, the payback periods remain about the same.

3.6 CONCLUSION

This paper focuses on three issues related to the adoption of a carsharing system in Beijing, China. First, this study develops a carsharing mode share split estimation model which is evaluated for accuracy with survey statistics and results. Using this model, the potential mode split was estimated based on 324 different kinds of scenario related to travel distance, number of travelers, rate of non-public transit users, rate of non-private sheltered mode users, rate of no car ownership, and three different cost structures (C, D, E). The estimated carsharing mode split ranges 9 to 32%. This mode split range is consistent with previous research (Hampshire and Gaites 2011).

Secondly, this paper estimates fleet size based on the estimated carsharing mode split from realistic scenarios. Three fleet types- an EV fleet with level 2 chargers, an EV fleet with level 3 chargers, and a CV fleet- were considered. Level 1 chargers were not considered because of their long charging times. A 15 km radius zone was targeted for the simulation, which included the number of stations, arrival time, travel distance, travel speed by arrival time, recharging, and fueling times. The simulation revealed that an EV fleet with level 2 chargers needs a bigger fleet than an EV fleet with level 3 chargers or a CV fleet. This is because level 2 chargers require longer recharging times and vehicles are unavailable for a period of time on return from previous trips. With little previous research about EV fleet types with different classes of chargers (Barth and Todd 1999, Schuster, Byrne et al. 2005, Kitamura 2009, Ciari, Schüssler et al. 2010, Fassi, Awasthi et al. 2012), this paper makes an important contribution in this growing area.

Last, annual economic performance was estimated using cost components such as infrastructure, vehicle depreciation, maintenance, fuel, and revenue. An economic analysis helped determine the appropriate fleet type based on the payback period for recovering the sunk costs. The results

show that an EV fleet with level 3 chargers is not appropriate for Beijing because it takes more than 10 years to recover the sunk costs. And a CV fleet does not make sense because of high gasoline prices and high vehicle maintenance costs. That leaves an EV fleet with level 2 chargers. After 5 years, it recovers the sunk costs and begins to profit.

While these figures are important, business operation costs such as office rent, telematics technology for shared vehicles, computer supplies, credit card processing, office product, labor costs, telecom, advertising, and utilities were not included. Parking was assumed to be freely provided as well. These costs are considered constant across fuel technologies, and do no differentially impact EVs compared to CVs. However, they would influence the overall economics of carsharing. Future research stemming from earlier studies of carsharing parking and depot optimization may address these other costs (Shaheen, Schwartz et al. 2004, Shaheen, Cohen et al. 2010, Correia and Antunes 2012).

Although this research does not consider positive external impacts from EV usage (e.g., car ownership, environmental externalities, etc.) instead of CV usage, this study strongly suggests that carsharing is not a business that can make a strong profit under the proposed cost models and competitive mode categories. But transportation policies regarding carsharing could help mitigate environmental issues and reduce dependence on imported fuel. These external benefits could justify subsidies.

This study builds a model to predict carsharing mode splits and estimated fleet sizes. It uses a simulation to explore demand and then performs an economic analysis for cost effectiveness with a range of variables. And while it explores carsharing systems' feasibility and appropriate fleet size and type, the study's limitations create many possibilities for future research. Since this

study considers only three cost structures, there is no examination of differing fares for EVs and CVs that could incentivize people to use EVs. This study also assumes a homogeneous fleet of carsharing vehicles, where a mix of vehicles, fuels, and charging infrastructure could perform better. Moreover, future study may include environmental externalities in the analysis.

4 ELECTRIC VEHICLE (EV) FLEET OPTIMIZATION: A CASE STUDY OF THE UNIVERSITY OF TENNESSEE, KNOXVILLE MOTOR POOL

ABSTRACT

Managing a fleet efficiently to addresses demand within cost constraints is a challenge. Mismatched fleet size and demand can create suboptimal budget allocations and inconvenience users. To address this problem, many studies have been conducted around heterogeneous fleet optimization. That research has not included an examination of different vehicle types with travel distance constraints. This study focuses on optimizing the University of Tennessee (UT) motor pool which has a heterogeneous fleet that includes EVs with a travel distance and recharge time constraint. After assessing UT motor pool trip patterns, a Queuing model was used to estimate the maximum number of each vehicle type needed to minimize the expected customer wait time to near zero. The break-even point is used for optimization model to constrain the minimum number of years that electric vehicles should be operated under the no subsidy assumption. The models are very flexible and can be applied to a wide variety of fleet optimization problems. It can help fleet managers make decisions about fleet size and EV adoption. In the case of UT's motor pool, the results show that the fleet has surplus vehicles. In addition to reducing the number of vehicles, total fleet costs could be minimized by using electric vehicles for all trips less than 100 miles.

4.1 INTRODUCTION

Managing a fleet efficiently to addresses demand within cost constraints is a challenge. A fleet management program balances many objectives including driver management, speed management, fuel management, route management, fleet size and composition management. If those objectives are not balanced, users may be inconvenienced and total fleet costs could be suboptimal. This study examines fleet size and composition management, with a focus on the role of electric vehicles (EVs) in corporate passenger car fleets. Several earlier studies have examined fleet size and composition management, but none have addressed the unique operational characteristics of EVs in fleet optimization.

Recently, EVs have emerged as an alternative fuel vehicle that can address many sustainability challenges. With low emissions and lower operating costs (fuel and maintenance) than conventional vehicles (CVs), they are becoming more popular in commercial uses (Funk and Rabl 1999). This is despite the vehicles' significantly different performance characteristics and fixed costs, such as purchase price, depreciation, refueling infrastructure, and registration fees. An EV's purchase price is higher than a CV's purchase price, but this can be balanced by variable costs like fuel, insurance, and maintenance costs. An EV's variable costs are significantly lower than a CV's. Beyond costs, EVs' commercial success is impacted by two additional characteristics: their short driving distance and long refueling (recharging) time. EVs need to be driven often for the fuel cost savings to overcome the high fixed costs. Range and recharging time constrain an EV owner's ability to maximize EV use and economic performance.

Vehicle fleets offer a unique opportunity to manage supply and demand by assigning the appropriate vehicle technology (CV or EV) for each trip. Despite that, most vehicle fleets currently rely on gasoline internal combustion engine vehicles, CVs (Samaras and Meisterling

2008). But EVs could easily be integrated into existing fleets. First, fleets usually have centralized parking and dispatch locations that could readily incorporate an EV charging infrastructure. Secondly, with customer's frequent short trips, EVs could have high utilization rates. Third, with known trip distance and duration, managers can appropriately match vehicle type to individual trips.

This chapter develops an optimization framework for corporate fleet adoption of EVs, this includes developing a model for overall fleet size and the appropriate mix of EVs and CVs. The chapter focuses on the University of Tennessee (UT) motor pool, which is located to Knoxville, Tennessee. UT motor pool serves the transportation needs of faculty, staff, and students conducting official business. This study applies fleet optimization methods to investigate the trip patterns of UT motor pool and find how many of those trips are EV compatible. Optimized fleet size, compositions, and required operating years are the objective values with cost constraints in the optimization model.

4.2 BACKGROUND

4.2.1 Electric vehicle

The transportation sector has developed plug in battery EVs and other technologies in recognition of the importance of fuel consumption and energy security, economic efficiency, health concerns, and environmental impacts (Wirasingha, Schofield et al. 2008). EVs (defined as battery EVs here) rely solely on battery power charged through a charging station. Balancing expensive and heavy battery capacity requirements with expected range usually results in commercial EVs with lower driving range than an equivalent CV (Lester B. Lave 1995).

EVs have existed for more than 150 years (Lixin 2009). Because of production efficiencies and easily available, cheap fossil fuel, CVs became widespread through the 20th century. In recent decades, battery technology improvements have allowed for improved EV designs. The industry has developed more energy efficient and less polluting EVs (Lixin 2009). Using electricity and without tailpipe emissions, EVs can help reduce operating costs and fuel consumption (Shiau, Kaushal et al. 2010). EVs' popularity can be attributed to its potential for reducing a country's dependence on imported petroleum and its greenhouse gas (GHG) emissions (Taylor, Maitra et al. 2009). This GHG reduction holds even when balancing EVs increased electric consumption that causes increased pollution from electricity generating sources (Funk and Rabl 1999). Thus recent commercialized EVs have been relatively successful with markets in the United States, Europe, and China where a new energy vehicle policy subsidizes EV deployment.

Because costs, driving range, fuel efficiency, vehicle gross weight, and other factors differ from EVs to CVs, fleets must precisely determine its vehicles' needed specifications and characteristics. Even though the EVs' purchase price is higher than that of gasoline or diesel vehicles, other variable costs like fuel, maintenance and coupled with purchase subsidies, the registration with incentive, insurance, maintenance, repair, and energy price of EVs are lower than those of CVs.

This study introduces and analyzes one commercialized EV, the Nissan Leaf, because of its publically available specification and performance information. The Nissan Leaf has an 80kW AC synchronous electric motor, a 24kWh lithium-ion battery, a 3.3kW onboard charger, and a battery heater. The Environmental Protection Agency (EPA) LA-4 city cycle laboratory tests determined it has a driving range of up to 100 miles. Based upon EPA five-cycle tests, using varying driving conditions and climate controls, the EPA has rated the Nissan LEAF at a driving

range of 73 miles. EPA MPG equivalent is 106 (city) and 92 (hwy) miles (Nissan USA n.d.). This study assumes that EV can drive up to 100 miles.

4.2.2 EV benefits compared to CV

In general, CVs contribute to local air pollution, noise pollution, water pollution, and other pollution. Air pollution may cause reduced visibility, crop losses, material damage, forest damage, climate change and human health impacts (Delucchi 2000). CVs emit many kinds of exhaust pollutants such as particulates, hydrocarbons, nitrogen oxides (NOx), carbon monoxide (CO), carbon dioxide (CO2), and other pollutants. The emissions can either affect the environment directly through diminished air quality and climate change or be precursors to species of concern, which are formed in the atmosphere. The former includes carbon monoxide (CO), and the latter includes volatile organic compounds (VOCs) and nitrogen oxides (NOx) which are precursors to the photochemical formation of ozone and PM (Parrish 2006). Diesel vehicles have different emission characteristics than gasoline vehicles, e.g., NOx emission levels are higher for diesel vehicles (Rexeis and Hausberger 2009).

Older vehicles without advanced pollution control technology cause a significant amount of urban emissions. Some argue for an automobile replacement policy, where old cars need to be replaced by new ones to prevent continuous use of inefficient and higher-polluting vehicles. The retirement program sometimes incentivizes owners of older vehicles to replace old vehicles earlier (Dill 2004). Kim et al. (Kim, Keoleian et al. 2003) suggest that vehicle retirement should be decided by economic factors such as repair cost, market price, and scrap price of a used vehicle.

Previous research (Samaras and Meisterling 2008) concludes that the EVs can reduce 38-41% of GHG emissions compared to the CVs and 7-12% of the emissions compared to traditional hybrids. They find that the EV battery, especially lithium-ion battery material and production, accounts for 2-5% of an EV's life cycle GHG emissions. They also point out the importance of using electricity for energy which influences GHG emissions.

Emission factors for EVs are very sensitive to the time of recharging, the source of electricity, and the region an EV is charge (Hadley and Tsvetkova 2009). Coal (38%) is the largest share of electricity source followed renewable (20%), nuclear (17%), natural gas (16%), and oil (9%). Previous research expected the electricity production will be almost double by 2020. As more natural gas and nuclear power plants replace older coal power plants, this range should improve (Sims, Rogner et al. 2003).

4.2.3 Fleet optimization models

This paper builds on previous research to study how to utilize EVs in vehicle fleets; it develops a model based on fleet size and composition. The vehicle routing problem (VRP) serves as a precursor to the fleet optimization model. Proposed by Dantzig and Ramser in 1959, the VRP is a combinatorial optimization and integer programming approach seeking to service a number of customers with a fleet of vehicles (Crevier, Cordeau et al. 2007). Since its inception, numerous studies have used and developed the VRP. With several kinds of VRP, this study divides them into two categories: capacitated vehicle routing problem (CVRP) (Golden 1988, Toth and Vigo 2001, Baldacci, Toth et al. 2007, Crevier, Cordeau et al. 2007, Gendreau, Iori et al. 2008, Golden, Raghavan et al. 2008, Côté and Potvin 2009, Eksioglu, Vural et al. 2009, Laporte 2009, Thibaut Vidal 2012) and capacitated arc routing problem (CARP) that improves local search procedures (Golden and Wong 1981).

Some have focused on heterogeneous mixed fleet optimization by narrowing down from VRP and dispatch models. Several studies (Choi and Tcha 2007, Baldacci, Battarra et al. 2008, Baldacci and Mingozzi 2009, Prins 2009, Brandão 2011, Penna, Subramanian et al. 2013) have examined the heterogeneous VRP (HVRP). In the applications of HVRP, they tried to minimize total cost by dispatching each vehicle type, defined by its capacity, a fixed cost, a distance unit, and availability.

4.2.3.1 Freight fleet optimization

Company fleets must decide whether to own fleet vehicles or rent them. Etezadi and Beasley (Etezadi and Beasley 1983) found that optimal fleet composition for a central depot has to supply a specific number of customers. That study developed a model that optimized the number of owned and rented vehicles to minimize total costs based on distance travelled.

$$Minimize \sum_{j=1}^{m} \left(F_j x_j + \sum_{t=1}^{T} f_j y_{jt} \right) + \sum_{j=1}^{m} \sum_{t=1}^{T} \left(V_j z_{jt} + v_j w_{jt} \right) \tag{1}$$

F_j = Fixed cost associated with owning a vehicle of type j for T periods
f_j = Fixed cost associated with hiring a vehicle a vehicle of type j for one period
V_j = Variable cost of an owned vehicle of type j
v_j = Variable cost of a hired vehicle of type j
x_j = Number of owned vehicles of type j
y_{jt} = Number of hired vehicles of type j in period t
z_{jt} = Distance travelled by owned vehicle of type j in period t
w_{jt} = Distance travelled by hired vehicle of type j in period t

Other research was performed with six different size vehicles to optimize the size and composition. The aim of the linear model is to maximize profit and minimize total costs. The vehicle class is constrained by material and volume shipped. The developed model is shown in equation (2) (Gould 1969).

$$Minimize \text{ FYN} + \text{ V}\sum_{r} X_r\, f(d_r) + \text{V}\sum_{r} h_r\, f(d_r) \tag{2}$$

F = Fixed cost/day of a company-owned vehicle
V = Variable cost/day of a company-owned vehicle
H = Hiring cost/vehicle per day
Y = Number of working days in a year
N = Number of vehicles in the fleet
X_r = Number of loads carried by company vehicles on days when demand is d_r
h_r = Number of loads carried by hired vehicles on days when demand is d_r

4.2.3.2 Passenger fleet optimization

If the fleet is too small and cannot meet the demand, then many additional vehicles should be rented, at additional cost. To achieve the optimal fleet size, the cost to be minimized can be categorized into fixed and variable costs during the total life cycle. A novel algorithm combines dynamic programming and the golden section method to determine optimal fleet composition (Loxton, Lin et al. 2012).

$$\underset{p_1,\ldots,p_m}{Minimize}\left\{n\alpha_i p_i + \beta_i \sum_{j=1}^{n}\sum_{k=0}^{N_i} \theta_{ijk} min(k, p_i) + \gamma_i \sum_{j=1}^{n}\sum_{k=0}^{N_i} \theta_{ijk} max(k - p_i, 0)\right\} \tag{3}$$

M = Number of vehicle types
N = Number of periods in the time horizon
α_i = Fixed cost per period of a type-*i* vehicle
β_i = Variable cost per period of a type-*i* vehicle
γ_i = Hiring cost per period of a type-*i* vehicle
θ_{ijk} = Probability that *k* type-*i* vehicles will be required during period *j*
N_i = Maximum number of type-*i* vehicles required during a single period
P_{max} = Maximum fleet size

Previous research determines optimal fleet size and mix for paratransit service. It shows that fleets should not only meet diverse travel needs and seating requirement of their client, but also the decisions on how many vehicles and what types of vehicles to operate are made by managers on an ad hoc basis without much systematic analysis. The research approaches the optimization problem from the perspective of service efficiency with cost-effectiveness. Another research

proposed a heuristic procedure which can be used in paratransit companies' specific operating conditions and environments (Fu and Ishkhanov 2004).

The model to optimize buy, operate, and sell policies for fleets of bus transit vehicles was developed. The model below minimizes the total discounted cost over L years which is equal to the purchase price minus reward from selling plus the cost of operating the buses (Simms, Lamarre et al. 1984).

$$Minimize\ \mathrm{Z} = \sum_{i=0}^{L} \alpha^i a_i A_i - \sum_{i=0}^{L} \alpha^{i+1} \sum_{j} \left(n_{ij} - n_{i+1.j+1}\right) S_{i+1.j+1} + \sum_{i=0}^{L} \sum_{j} \alpha^i n_{ij} C_{ij}\left(m_{ij}\right) \tag{4}$$

L = Length of planning horizon in years
A_i = Cost of acquiring a new bus in year *i*
a_i = Number of new buses acquired at the beginning of year *i*
n_{ij} = Number of buses j years old operated during year *i*
m_{ij} = Number of route kilometers travelled by a bus *j* years old in year *i*
$C_{ij}(m_{ij})$ = Cost of operating a bus *j* years old in year *i* for m_{ij} kilometers (for discounting purposes, operating costs incurred during the year are treated as occurring at the beginning of the year)

Previous research also developed an optimization model that minimizes life cycle cost, petroleum consumption, and GHG emissions for conventional, hybrid, and plug-in hybrid vehicles under several scenarios. They concluded that high battery costs, low gas prices, and high electricity prices drastically reduced the financial viability of plug-in EVs (Shiau, Kaushal et al. 2010).

There have been two studies for the University of Tennessee Motor pool fleet. Even though the data and information are old, these studies show the UT motor pool's history. Early research in 1980 found that the UT motor pool's vehicle request rates were time-dependent and non-stationary Poisson processes. Over 85% of the trips were five days or less. Also, the research did

regression analysis for check out duration and distance travelled. It shows a strong linear relationship with 0.92 R^2 (total trip mileage by length of trip). Service level and fleet utilization metrics were used to assess the motor pool's service capability (Fowler 1980). A different study pointed out that increasing the fleet reduces the number of unsatisfied requests, but increases the fixed investment in the motor pool. Also, they found that the peak for checking out vehicles is early in the week and that the demand decreases later in the week. The check out duration followed an exponential distribution (Williams and Fowler 1979).

4.3 DATA ANALYSIS

4.3.1 UT motor pool data description

The UT motor pool was set up in the early 1950's and stayed relatively small in scale for over a decade. In 1960's the University experienced a sharp enrollment increase and requests for dispatch vehicles grew rapidly. So a large number of vehicles were added to the fleet to satisfy the increasing demand (Fowler 1980).

Over the years many procedures have been implemented to maintain UT motor pool vehicles. Users are encouraged to use an on-site fueling station or a fleet fueling card at participating gas stations. The vehicles are maintained and repaired in-house except in cases of severe damage when the vehicles serviced outside. Any vehicles older than three years or that have traveled 80,000 miles, whichever is first, are sold through public auctions each spring.

This study examines data collected between March 14, 2011 and February 20, 2012. The fleet consisted of 95 mid-size gasoline sedans that made a total of 1,937 trips. The sedans were 2008-2011 Dodge Avengers and 2011 Ford Fusions. The rated fuel economies (averaged over 4 model years) ranged from 20 - 22 miles per gallon (mpg) for city and 28.5 - 30 mpg for highway. Since

only mid-size sedans can be potentially replaced by EVs such as the Nissan Leaf, only those fleet data were analyzed.

4.3.2 Data analysis

To assess the trip patterns of the UT motor pool vehicles, this study analyzed the times at which the vehicles were checked out, the distance traveled, and the destinations from the given data (Table 4-1). The median value of checkout duration and distance traveled are 70 hours (3 days) and 409 miles, respectively.

Table 4-1 UT motor pool check-out pattern

	85%tile	50%tile	15%tile	Max	Min	Median
Using time (hours)	113	51	21	293	1	70
Travel Distance (mile)	662	392	169	1,220	11	409

Around 40% of the total trips are local, meaning that the destinations were in counties bordering the UT campus in Knoxville. The destinations of 79% of the trips are within the state of Tennessee. The longer duration of checkout times reflects overnight or weekend checkouts. Figure 4-1 shows the frequency of the number of vehicles checked out at a given time. The most frequent number of simultaneously checked out vehicles is 43 and the average is 20~25 vehicles. This will be used to evaluate the model suggested in this chapter. About 96% of demand is met by 30 vehicles.

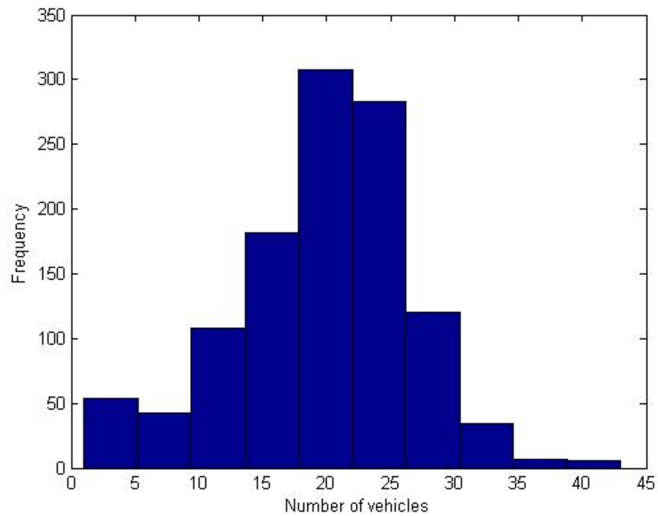


Figure 4-1 The frequency of number of vehicles checked out simultaneously

4.3.3 Cost descriptions

All costs are included as variables, since different fleets have different rules. For example, the University of Tennessee has no federal incentives, state incentives, taxes, or registration fees. However, the developed model must be a general cost model that can apply to all fleets.

4.3.3.1 Fixed costs

Fixed costs are the expenses that do not change as a function of the activity within the relevant period. This study includes MSRP (Manufacturer's Suggested Retail Price), which is the list price or recommended retail price of the vehicle. The MSRP for the Dodge Avenger, which is used in the UT Motor pool, and the Nissan Leaf are $19,900 and $35,200, respectively. In the state of Tennessee, a 7% sales tax makes the final prices $21,293 and $37,644, respectively. The sales tax rates vary based on where the vehicles are registered. An additional factor for cost is an incentive that the Tennessee Department of Revenue offers, a rebate of $2,500 on the first 1,000 qualified plug-in EVs (PEV) purchased in Tennessee at EV dealerships (US Department of Energy).

4.3.3.2 Variable costs

Variable costs are expenses that may change by time or use rates. Maintenance costs include regular drivetrain maintenance, repair and tire, insurance costs, fuel costs, and registration. Every cost can be calculated by using NPV (Net Present Value) which is defined as the sum of the present values of the individual cash flows of the same entity.

$$NPV\ (r, N) = \sum_{n=1}^{N} \frac{C_i}{(1+r)^n} \tag{5}$$

n = the time of the cash flow

r = the discount rate (5% used here)

C_i = the annual costs

For the calculation of fuel costs, this research assumes the retail gasoline price is $3.25/gallon. It costs $0.13 per mile using the average of EPA mileage estimates, 25 MPG (21 City/29 Hwy). For example, when a Dodge Avenger travels 25,000 miles per year, the fuel cost is $3,250 per year. A Nissan Leaf can drive around 3 miles per kWh electricity. This research assumes the electricity price is $0.1/kWh and costs $0.03 per mile. Thus when a Nissan Leaf travels 25,000 miles annually, the fuel cost is $833 per year (about 25% of the Dodge Avenger's costs).

The depreciation rates by vehicle age and model are shown in Figure 4-2. Since the Avenger (launched in 2008) and the Leaf (launched in 2011) do not have a long history, four vehicles--the Dodge Avenger, the Ford Focus, the Toyota Prius, and the Nissan Leaf--were compared. The Ford Focus represents US manufactured vehicles and the Toyota Prius represents Hybrid vehicles. As expected, the depreciation rate for a hybrid vehicle is lower than that of gasoline

vehicles (KBB.com Web 2014). Unlike our expectation, the Nissan Leaf's depreciation rate is similar to the CV's depreciation rate, perhaps because of uncertainty with new technology

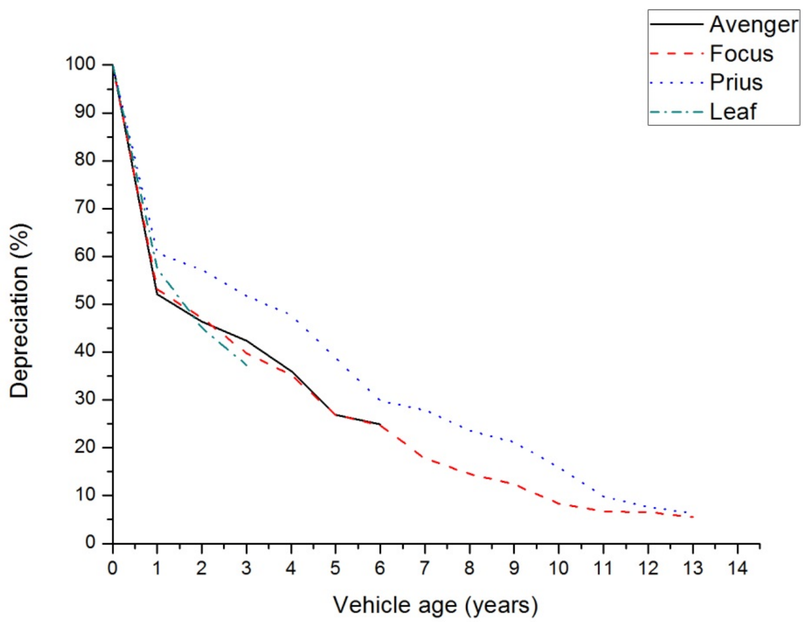


Figure 4-2 Depreciation rates by vehicle age and model

4.3.3.3 Break-even point

Because an EV's fixed costs, such as vehicle purchase, tax, and registration, are higher than those of CVs, the break-even point (BEP) is important. This is the point at which expenses and revenue are equal so there is no net loss or gain. At that point an owner has "broken-even." In this study, the BEP is set as the minimum time or mileage required before an EV can be resold. The EVs' total costs become lower than the costs of CVs after this point.

Table 4-2 shows the break-even point for a Nissan Leaf and a Dodge Avenger. This assumes the cars travel 20,000 miles per year and operate for 10 years while gasoline remains $3.25/gallon

and electricity is \$0.1/kWh. The EV break-even points (points of intersection in Figure 4-3) range from 3 to 5 years with different scenarios. The break-even point will be used for optimization model to set up a constraint of the minimum number of years that EVs should be operated under the no subsidy assumption.

Table 4-2 Break-even point

Assumptions	20,000 miles per year, Gasoline price: \$3.25/gal, Electricity price: \$0.10/kWh (10 years, 5% discount rate)			
	EV (Nissan Leaf)			CV (Dodge Avenger)
	No subsidy	Subsidy (TN)	Subsidy	
MSRP (\$)		35,200		19,900
Subsidy (\$)	0	2,500	7,500	0
Tax and registration (7%) (\$)	2,464	2,289	1.939	2,464
Total purchase price (\$)	37,664	34,989	29.639	21,293
Fuel cost/year (\$)		666.67		2,600.00
Maintenance costs (\$)		200 (\$0.01/mile)		1,600 (\$0.08/mile)
Depreciations		Similar pattern with Prius		Similar pattern with Focus
BEP (years)	4.82	4.10	2.61	

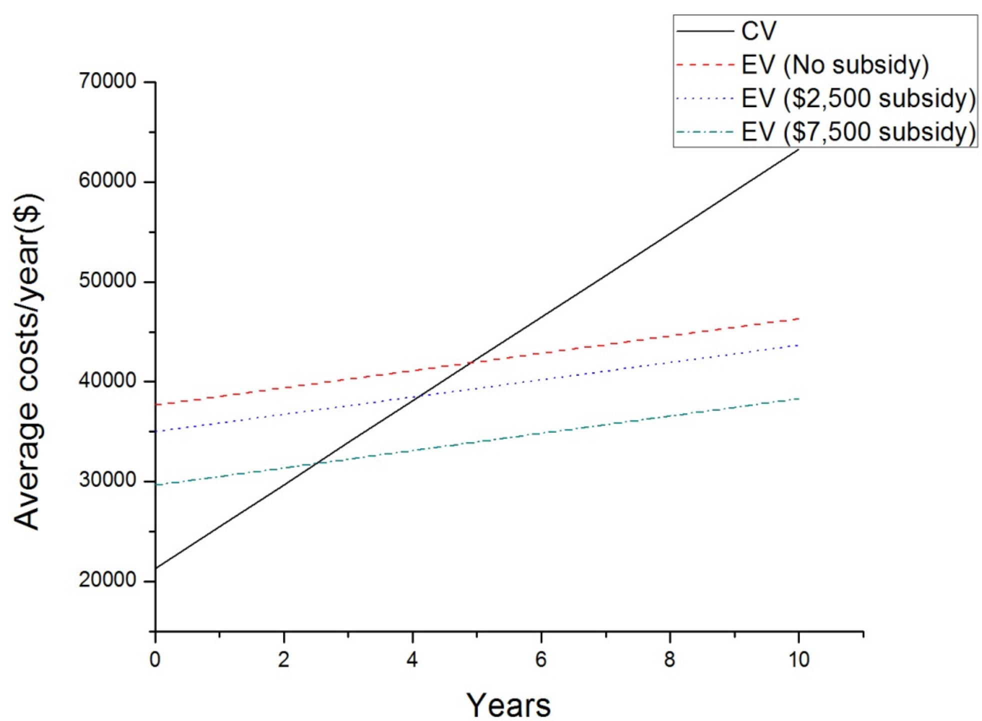


Figure 4-3 Break-even point (example)

4.4 QUEUING MODELING FOR FLEET SIZE

This study utilizes a queuing model to determine the optimized fleet size based on the number of trips and trip durations to meet 100% of the demand. This study assumes that the motor pool satisfies demands and makes the probability an arriving customer has to wait near zero. For fleet composition, this study extends that analysis to access the potential for EV s in the fleet. A Multiple-Channel Queuing model is appropriate to estimate the probability under the assumption that one vehicle plays a role as a server.

4.4.1 Queuing model

A multiple-channel customer queuing model is suitable and assumes a Poisson arrival rate with an Exponential distribution of service times. The model is described as follows (Stevenson and Hojati 2007).

When the service vehicles are composed of N number of vehicles, the customer of the system c can assume one of these:

1) $c \leq N$ there is no queue because all customers are being served.
2) $c > N$ a queue is formed of the length $c - N$

The utilization factor ρ is the ratio between the mean customer arrival rate λ (number of arrived people/unit of time) and service rate μ (number of people can be served/unit of time), therefore

The probability that there are c customers in system when c is less than N is:

$$P_{N_c} = \frac{1}{c!}\left(\frac{\lambda}{\mu}\right)^c P_{N_0} \; for\; c = 0,1,\ldots,N-1 \;\; i.e. \quad c < N \tag{6}$$

When the number of customers c equals or is greater than the number of vehicles N, this probability becomes:

$$P_{N_c} = \frac{1}{N!\,N^{c-N}} \left(\frac{\lambda}{\mu}\right)^{c} P_{N_0} \; for \; c \geq N \tag{7}$$

The probability of having no customers in a multiple-channel system is:

$$P_{N_0} = \left[\sum_{i=1}^{N-1} \frac{1}{i!}\left(\frac{\lambda}{\mu}\right)^{i} + \frac{1}{N!}\left(\frac{\lambda}{\mu}\right)^{N} \frac{\mu N}{\mu N - \lambda}\right]^{-1} \tag{8}$$

The probability that a customer approaching the vehicles has to wait to be serviced coincides with the probability that there is N or more, customer in the system:

$$P_{N_c} = \frac{\mu\left(\frac{\lambda}{\mu}\right)^{N}}{(N-1)!\,(\mu N - \lambda)} P_{N_0} \tag{9}$$

The mean length of the waiting line, or average queue length, excluding the customers being served, is calculated by multiplying equation (9) by the ratio $\frac{\lambda}{\mu N - \lambda}$:

$$m_Q = \frac{\lambda\mu\left(\frac{\lambda}{\mu}\right)^{N}}{(N-1)!\,(\mu N - \lambda)^{2}} P_{N_0} \tag{10}$$

The average number of customers in the system is:

$$m_N = \frac{\lambda\mu\left(\frac{\lambda}{\mu}\right)^N}{(N-1)!\,(\mu N-\lambda)^2}\,P_{N_0} + \frac{\lambda}{\mu} \tag{11}$$

The average waiting time of a customer who has successfully checked out a vehicle is:

$$W_Q = \frac{\mu\left(\frac{\lambda}{\mu}\right)^N}{(N-1)!\,(\mu N-\lambda)^2}\,P_{N_0} \tag{12}$$

The total average time that a customer travels with the vehicle, which is sum of the average waiting time and average vehicle usage time (the reciprocal of service rate) is:

$$W_N = \frac{\mu\left(\frac{\lambda}{\mu}\right)^N}{(N-1)!\,(\mu N-\lambda)^2}\,P_{N_0} + \frac{1}{\mu} \tag{13}$$

The number of vehicles that makes the probability that a customer approaching the vehicles has to wait to be serviced near zero feeds into the fleet optimization model by constrain to limit the maximum fleet size. The total travel time is used to evaluate the model validity with real trip patterns.

4.4.2 Queuing results

According to the data collection, a total of 1,936 trips were made in 344 days. Each weekday averaged 7.9 trips. However, it is not easy to determine the number of vehicles that the motor

pool needs based solely on the number of daily trips. Many other factors are important, for example the duration of checkout (particularly for multi-day use).

This study assumes that the distribution of the arrival rate of customers is Poisson and the service time follows the Exponential distribution (Stevenson and Hojati 2007). As a multiple channel queuing model, the aim is to make the probability that an arriving customer has to wait near zero. As the number of vehicles increases, the probability goes down. Figure 4-4 indicates how long a single arrival will have to wait. For example, if the fleet only has 10 vehicles, there is nearly 100% probability that at least one customer will have to wait. When the fleet has 51 vehicles, the probability approaches zero.

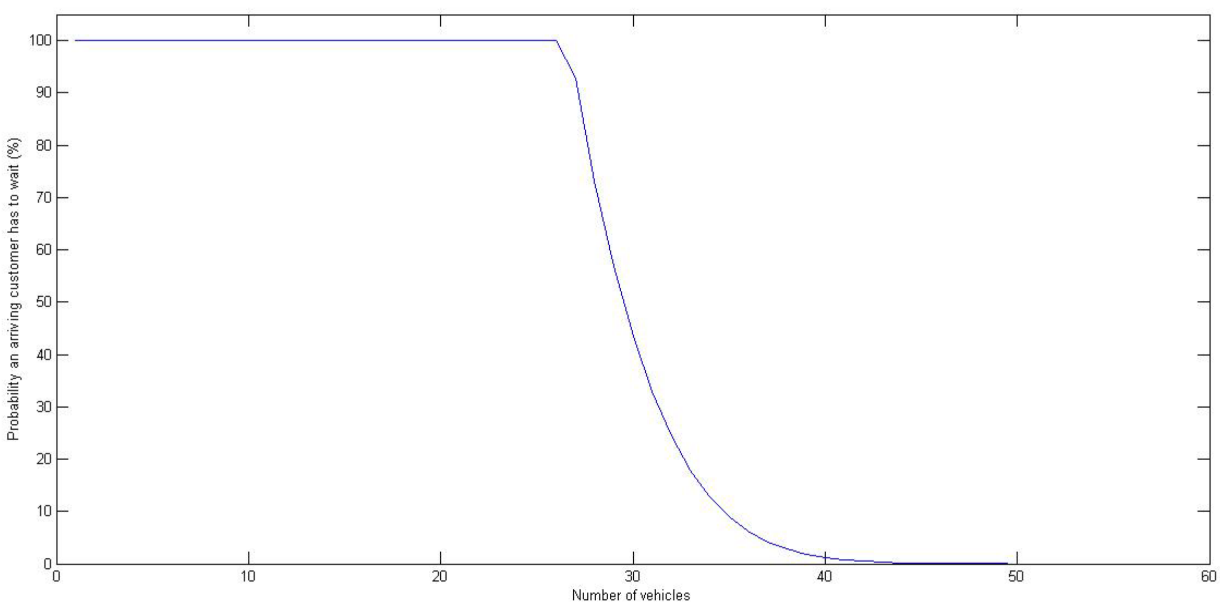


Figure 4-4 Probability an arriving customer has to wait in queuing theory

The average number of customers, which is the average number of vehicles that are checked out during peak times, is 27.7; and the average time a customer spends in the system is 3.5 days according to the equations in queuing model. The number of vehicles that is calculated by the queuing model looks reasonable compared with the number of vehicles that had checked out simultaneously and the considerations of vehicles' maintenance and repair time. The maximum fleet size is 51 vehicles.

This study uses the queuing model for trips of less than 100 miles, which are suitable to be replaced by EVs. The result indicates that 7 CVs can be replaced by EVs to maintain the probability that an arriving customer has to wait near 0%. This means the users who travel less than 100 miles will not need to wait to use EVs when the fleet has 7 EVs. If the number of EVs is more than the estimated number, the fleet has redundant EVs that cannot meet the demand requiring a CV.

A related question is whether 44 CVs can satisfy all the other trips (not including those less than 100 miles that can use an EV). The probability that an arriving customer has to wait is near 0%, and the given numbers of EVs and CVs used as constraints from the queuing model are well estimated. Therefore, this study sets the maximum number of EVs at 7 and the maximum fleet size at 51 (44 CVs) for the optimization model. With these constraints, the following chapter describes the optimization model that minimizes total costs.

4.5 FLEET COMPOSITION OPTIMIZATION

In this section, the total fleet size is set at 51 (as estimated in the previous section). Assuming that the fleet may adopt EVs, what is the optimal fleet composition? To estimate what portion of CVs can be replaced by EVs (with a constraint maximum of 7 EVs), the model should be optimized while minimizing total cost. Then, the model is:

<u>Decision variables</u>

P_k	The number of *k*-type vehicle
A_k	The estimated life for *k*-type vehicles

<u>Fixed costs</u>

α_k	The purchase price of *k*-type vehicle
β_k	The incentive of *k*-type vehicle
γ_k	The vehicle purchase tax rate of *k*-type vehicle

<u>Variable costs</u>

N_{ik}	The number of *k*-type vehicle in year *i*
TM_{ik}	The travel mileage of *k*-type vehicle in year *i*
δ_{ik}	The insurance costs per year of *k*-type vehicles in year *i*
m_{ik}	The maintenance costs per mile of *k*-type vehicles in year *i*
fc_{ik}	The fuel costs per mile of *k*-type vehicle in year *i*
ω_{ik}	The annual registration fee of *k*-type vehicle in year *i*

<u>Resale value</u>

S_{ik}	The number of *k*-type sold vehicle in year *i*
φ_{ik}	The resale value of *k*-type vehicles in year *i*
R	The break-even point

$$Minimize \sum_{k=1}^{K} P_k(\alpha_k - \beta_k)(1+\gamma_k) + \sum_{i=0}^{A_k-1}\sum_{k=1}^{K}\{N_{ik}(\delta_{ik}+\omega_{ik}) + TM_{ik}(m_{ik}+fc_{ik})\} - \sum_{i=0}^{A_k-1}\sum_{k=1}^{K} S_{ik}\varphi_{ik} \tag{14}$$

Subject to:

$$P_k, A_k \geq 0, \forall k \tag{15}$$

$$P_k, A_k = integer, \forall k \tag{16}$$

$$N_{ik} \leq \sum_{k=1}^{K} N_{ik}, \forall i \forall k \tag{17}$$

$$N_{ik} = N_{i-1k} + P_{ik} - S_{ik} \tag{18}$$

$$S_{ik} = 0, i = 0, \forall k \tag{19}$$

$$N_{i1} \le the\ value\ in\ the\ queuing\ model,$$
$$P_{N_0} = \left[\sum_{i=1}^{N-1} \frac{1}{i!}\left(\frac{\lambda}{\mu}\right)^i + \frac{1}{N!}\left(\frac{\lambda}{\mu}\right)^N \frac{\mu N}{\mu N - \lambda}\right]^{-1} \tag{20}$$

$$\sum_{k=1}^{K} P_{jk}(\alpha_k - \beta_k)(1 + \gamma_k) - \sum_{k=1}^{K} \sum_{i=0}^{A_k-1} (S_{ik}\varphi_{ik}) \le B_i, \forall i \tag{21}$$

$$\sum_{i=0}^{A_k-1} TM_{ik}m_{ik} \le \sum_{i=0}^{A_k-1} (\varphi_{ik}), \forall k \tag{22}$$

$$A_k \ge R_{(1,A_k)} = \left| (\alpha_1 - \beta_1)(1 + \gamma_1) - (\alpha_k - \beta_k)(1 + \gamma_k) \div \left\{ \begin{array}{l} \sum_{k=1}^{1} \sum_{i=0}^{A_k-1} (\delta_{i1} + TM_{i1}(m_{i1} + fc_{i1}) + \omega_1) - \\ \qquad \sum_{k=A_k}^{A_k} \sum_{i=0}^{A_k-1} (\delta_{ik} + TM_{ik}(m_{ik} + fc_{ik}) + \omega_k) \end{array} \right\} \right| \tag{23}$$

The objective function (14) minimizes the total costs associated with fixed costs, variable costs, and resale value with discounted cash flows. Since the UT motor pool fleet is a self-insured fleet, this study assumes that the average insurance rate reflects expected losses. The constraints (15) and (16) require a non-negative and integer solution for all decision variables.

The constraints given in (17) through (20) are the number of vehicles constraints. Constraint (17) enforces the total number of *k*-type vehicles in year *i* could not exceed the total number of vehicles in year *i*. Constraint (18) ensures that the total number of *k*-type vehicles in year *i* should be equal to the gap between number of purchased and sold *k*-type vehicles in year *i*. Constraint

(19) ensures that the fleet cannot sell a vehicle that is less than one year old. Constraint (20) assures that the number of EVs could not exceed the value attained in the queuing analysis presented above, which assures full availability of the fleet.

The constraints given in (21) through (22) are costs constraints. Constraint (21) limits total spending in *i* year so it will not exceed the fleet budget. Constraint (22) enforces that total annual maintenance costs should not exceed the resale value. Fuel costs are calculated by using fuel efficiency such as mile per gallon and mile per kWh and average fuel price per unit (gallon or kWh).

Constraint (23) enforces that the minimum estimated life for *k*-type vehicles in year *i* should be longer than the break-even year, assuring that the increased capital cost of EVs are recovered in fuel and maintenance savings before resale.

4.6 RESULTS

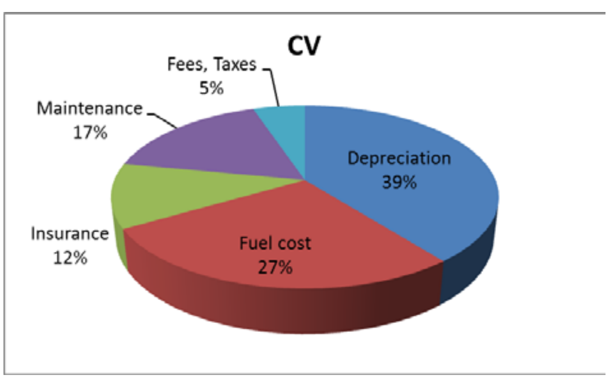
The optimization model was built using IBM ILOG CPLEX Optimization studio 12.5. The computer is a laptop with an Intel Core i5-3210M CPU @ 2.50 GHz with 6 GB of RAM memory. The time spend to generate a solution is 20.04 seconds.

4.6.1 Optimized fleet size and composition

Table 4-3 Optimization results

	Number of vehicles	Travel mileage per year	Years need to be operated	Total costs/vehicle/year (resale value included)
EVs	7	10,218 miles	4.5	$ 6,062
Gasoline Vehicles	44	20,193 miles	3	$ 10,116

The number of vehicles assure near zero expected waiting delay is 51 from the queuing model. The optimization results show that all trips less than 100 miles can be replaced by EVs with minimum total costs and those EVs should be operated for at least 4.5 years, which is later than the break-even point. Average annual total mileages estimated by the model appear reasonable compared with real data and the sum of total mileage satisfies the total fleet mileage demands. The total cost of ownership would be minimized with the estimated values in Table 4-3, which means that the fleet can be operated with a minimized budget when 7 EVs and 44 CVs are operated for 4.5 and 3 years, respectively. The detailed breakdown by year is shown as Figure 4-5. It shows that even though EV depreciation rate is lower than CV depreciation, depreciation costs account for the biggest portion of EV's average total costs per year because of high purchase price and low fuel and maintenance costs. It also shows the differences for maintenance and fuel costs. Fuel and maintenance costs for a CV account for 27% and 17% respectively. On the other hand, for an EV they account for only 6% and 2% for EV. This indicates that fuel price and efficiency are the most significant factors for a CV while a subsidy incentive to lower high purchase price is the most significant factor to promote EV usage.



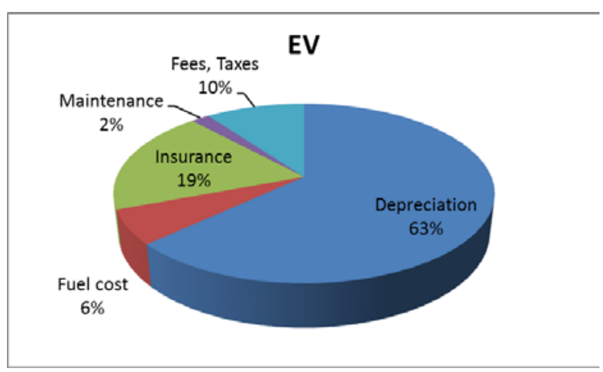


Figure 4-5 Detailed breakdown of cost elements by EV and CV per year

4.6.2 Sensitivity analysis

We now examine the sensitivity analysis for change of years that need to be operated. EVs need to be operated a minimum range of 5 to 10 years while CVs have a minimum range of 3 to 5 years. That is, EVs and CVs should be operated for at least 5 and 3 years, respectively. An EV can be operated up to 10 years and a CV may be used up to 5 years to satisfy the minimum total costs condition.

We use 3 different fuel efficiencies for each vehicle type to investigate how model sensitivities are affected by fuel efficiency. CVs require 22 miles per gallon (mpg), 25 mpg, and 50 mpg, the highest fuel efficiency for the Toyota Prius, a hybrid vehicle. EVs have a higher purchase price and efficiency ranges (mile per kWh) are 2 mi/kWh, 3 mi/kWh, and 4 mi/kWh. As shown in Figure 4-6, the EV requirement years to minimize total costs increase as CV mpg improves. That is, EVs become less competitive with the adoption of improved fuel efficiency CVs like traditional hybrids. CV required operating duration remains 3 years. Due to increased maintenance costs and decreased depreciation cost, the fleet would improve by selling old vehicles and buy new ones to minimize total fleet costs. The EV fuel efficiency scenarios do not differ much because of low fuel cost for EVs.

Figure 4-7 illustrates vehicle costs per year according to each scenario. Across all the scenarios, EVs' total costs are less than those of gasoline vehicles. In addition, even though the mile per kWh improved, the total costs for EVs do not decrease significantly because maintenance and repair costs exceed electricity costs. In contrast, CVs show a different pattern. The improved fuel economy decreases total costs. CVs are sensitive to gasoline price or fuel economy while EVs' mean total costs are not much affected by electricity price or mi/kWh. Unlike comparison with CVs, the total costs for EVs increased when the mile energy efficiency improved compared to

hybrid vehicles. This reflects the longer duration of time EVs are kept in the fleet and a hybrid vehicle's lower depreciation rate (when compared to CVs).

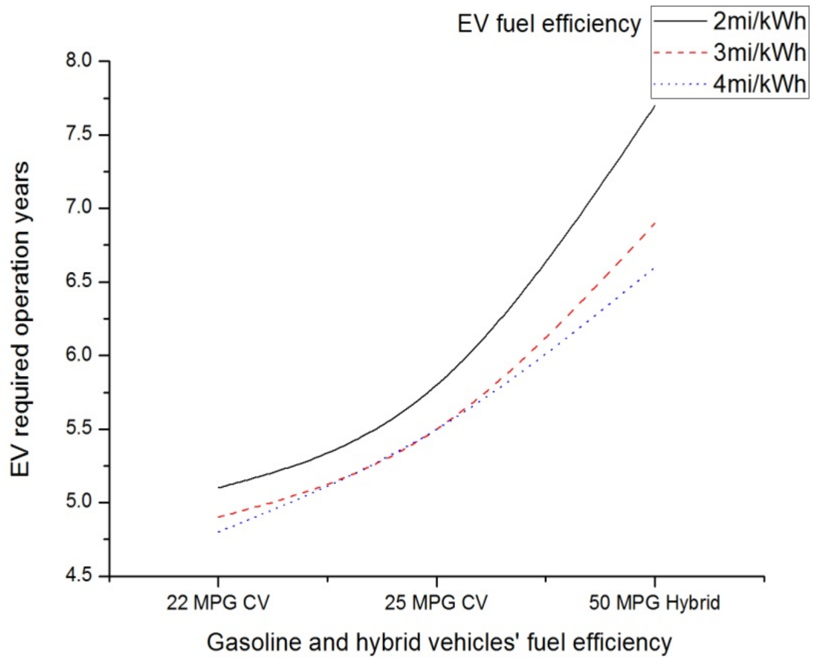


Figure 4-6 EV required operating years against mi/kWh and mpg to break even with CV

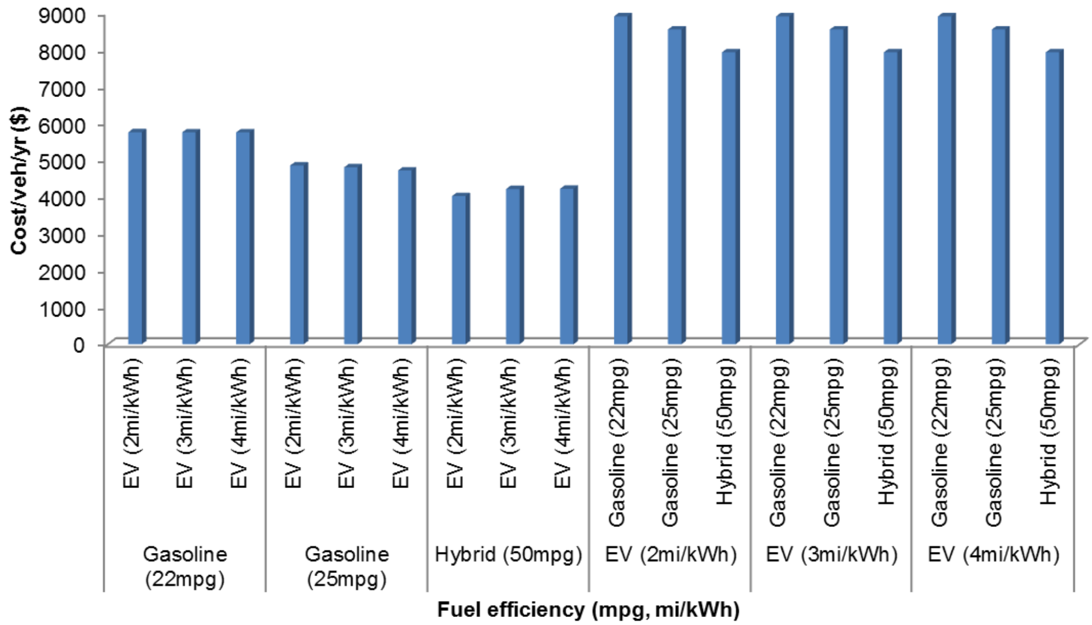


Figure 4-7 EV and CV total annual costs for each scenario

4.6.3 Buy and sell plan

To transition to a fleet that has maximum number of EVs, one should identify a replacement policy to purchase new vehicles. Both the UT buy and sell policy and results here indicate that a CV can be sold after 3 years. However, the current UT motor pool fleet has 44 surplus vehicles in its fleet. When vehicles are replaced, the point of contact in Figure 4-8 is important, but the fleet needs to sell the surplus vehicle minimize cost. This means determining the year that has the maximum price gap between resale value and ownership costs. The fleet minimizes its costs by selling the vehicle at its peak resale value in its first year. The fleet would better to replace new vehicles rather than the ownership costs exceed vehicle resale value. Figure 4-8 shows that the intersection of two lines, resale value and ownership costs, is just after 3 years.

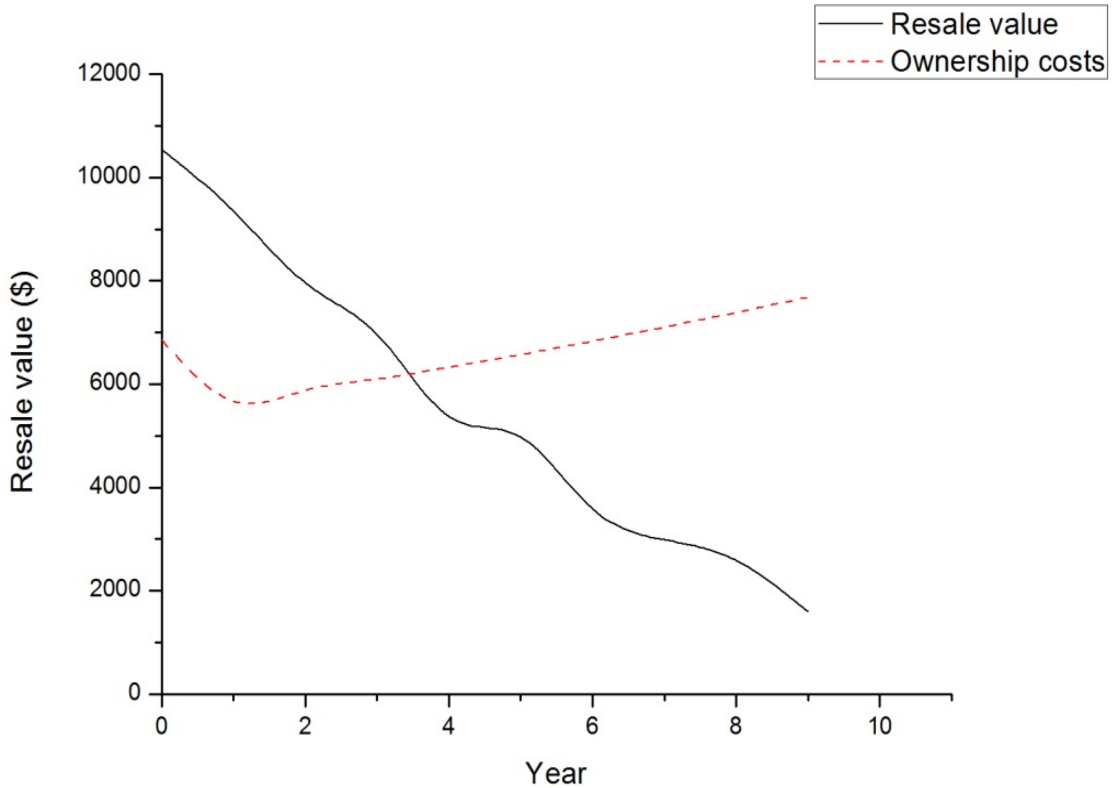


Figure 4-8 Relationships between resale value and ownership costs (CV)

Table 4-4 shows a proposed buy and sell plan based on the vehicle ages in the UT motor pool fleet and the suggested policy. Currently, UT motor pool vehicles range from 1 to 4 years old: 30 vehicles (1 year old), 46 vehicles (2 years old), 8 vehicles (3 years old), and 11 vehicles (4 years old). This study suggests that the 44 surplus gasoline vehicles (30 vehicles (1 year old) and 14 vehicles (2 year old)) should be sold in year one to minimize cost by maximizing resale value. EVs should be bought in year two while selling 32 vehicles (currently 2 years old) to achieve the optimized fleet size and composition. Once at the optimized size and composition, 5 years for EVs, 3 years for CVs that were estimated in the optimization model, a standard replacement policy can be followed. Figure 4-8 shows the optimum buy and sell policy through the transition

to the optimum fleet size and the recurring replacement policy. This can be adjusted to reflect annual budgets as needed (e.g., staggering recurring replacements to reflect relatively even yearly flows).

Table 4-4 Buy and sell plan

		Year															
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Buy	EV			7				7					7				
	CV			25	8	11		25	8	11		25	8	11		25	
Sell	EV							-7				-7				-7	
	CV		-44	-32	-8	-11		-25	-8	-11		-25	-8	-11		-25	-8
Total		95	51	Achieve optimized fleet size and composition													

4.7 CONCLUSIONS

The purpose of this study has been to determine optimized fleet size and composition through queuing and optimization modeling. While in recent years, many research projects have developed fleet size and composition optimization models, none of these studies consider EV adoption with its unique constraints (Gould 1969, Etezadi and Beasley 1983, Golden, Assad et al. 1984, Fu and Ishkhanov 2004). This study builds a queuing model to estimate the appropriate fleet size to satisfy demands, which means making the probability an arriving customer has to wait near zero. This model can estimate optimized fleet composition for a wide range of vehicle types with varying characteristic including purchase price, maintenance costs, fuel costs, travel distance, and refueling time. That information can help guide fleets as they adopt the EV or other alternative vehicles.

As shown by the queuing analysis and the optimization model, seven EVs could be introduced for trips of less than 100 miles. Trips longer than 100 miles could be handled by the remaining 44 CVs (if the motor pool is reduced to the recommended 51 vehicles). It is important to note

that this requires precise dispatching. It is possible that dispatching CVs for short trips will leave the EVs unable to meet demands for long trips, under peak demand scenarios.

This study explores annual breakdown cost components based on different EV and CV costs. This includes different depreciation rates from real market data. Even though an EV's depreciation rate is better than that of a CV, depreciation accounts for the largest part of EV costs. For CVs, fuel costs along with depreciation costs account for the largest part of CV costs. Sensitivity analysis shows CV is more sensitive to gasoline price changes for total costs.

There have been no studies about the UT motor pool fleet since 1980; this study analyzes recent data and then compares the old and new fleets. UT motor pool fleet size has increased since 1980 and the appropriate fleet sized needed to be re-estimated. The trip duration pattern remains 5 days or less for 85% of all trips (Williams and Fowler 1979, Fowler 1980). And a strong linear relationship between total trip mileage (mile) and duration (day or hour) also remains.

Results suggest that the UT motor pool may be inefficiently allocating resources. It currently operates with 95 sedans and this research shows that 51 vehicles can satisfy all demands while keeping the probability that an arriving customer has to wait at near zero. Indeed 30 vehicles could meet 96% of trips in the dataset. The fleet can save total annual cost of ownership and generate revenue from sold surplus vehicles. As shown in Figure 4-8, the highest ownership cost occurs during the first year because of sales tax and vehicle registration. The costs gradually increase after the second year as vehicles require more maintenance and repair, gas prices increase, and fuel efficiency decreases. When the fleet has the appropriate number of vehicles (meaning 44 fewer than it currently maintains), total annual ownership costs can be saved while maintenance is reduced and depreciation costs are minimized.

Future research could take this model and introduce more variables like service and waiting costs. This study assumes that fleet size should satisfy demands and it would be interesting to see about each demand satisfaction rate. EVs, CVs, and hybrid vehicles' specification and characteristics are changing and the research based on the considerations of those changes can be a good future research topic. Finally, allowing outsourced rentals (e.g., commercial rental cars) could be an area of further cost saving during peak demand times.

In this paper the queuing model helps determine constraints in the optimization model. Together they can determine effective fleet size and help plan EV adoption. The models are flexible enough to be used in a wide variety of fleet optimization problems. Using the queuing model has proven an effective approach to develop the constraint about EV's limited travel distance in the optimization model.

5 CONCLUSIONS

This dissertation consists of three separate but correlated topics: EV carsharing demand analysis and mode split forecasting; carsharing fleet optimization with EV adoption and economic analysis; and fleet size and composition optimization model development. The combination of carsharing and EVs may be one solution in the increasingly important quest to find sustainable transportation modes that mitigate transportation, environmental, and social issues.

First, this paper contributes to the feasibility of carsharing; it can be applied in urban cities like Beijing, China. Urban cities with well-developed public transit networks and relatively low user cost need to focus on the problem of carsharing costs. The most significant factor to carsharing remains the cost gap. Carsharing can be an alternative mode for taxi users because it has a competitive fare. Interest in one-way and roundtrip carsharing declined as the cost gap increased. People who already own cars find carsharing useful for one-way trips. On the other hand, carsharing is more often considered for home-based round trips and the travel tends to be in groups for those who do not own cars. Some demographic information including gender, age, gated apartment resident, and driver's license are significant in at least one of the models. Contrary to expectation, carsharing attributes including fuel type, branding, access time, and potential priority lane benefits are not significant in the carsharing models. The key finding here is that EVs by themselves are not more attractive that CVs. Also, to the extent that a large decal advertising that you are using a carshare vehicle is any indicator of status (positive or negative), had no influence on choice. Interestingly, people with high environmental concern are more interested in carsharing.

Secondly, the potential carsharing mode split was estimated using a statistical model based on 324 different scenarios related to travel distance, number of travelers, rate of non-public transit users, rate of non-private sheltered mode users, rate of households own no car, and three

different cost structures (C, D, E). The estimated carsharing mode split ranges from 9 to 32%. This paper also estimates fleet size based on the estimated carsharing mode split from realistic scenarios based on three fleet types: an EV fleet with level 2 charging infrastructure; an EV fleet with level 3 charging infrastructure; and a CV fleet. As a result, this study suggests that a carsharing fleet in Beijing needs to adopt EVs with level 2 charging infrastructure despite the high sunk costs required to establish the charging infrastructure.

Finally, the University of Tennessee motor pool fleet is operating with more vehicles than the optimization model suggests and the queuing model recommends keeping the probability of customer wait time near zero. This could result in an inefficient allocation of resources. As shown by this analysis, all trips of less than 100 miles could use EVs rather than CVs. Approximately 7 EVs could meet demand for trips less than 100 miles at minimum total costs. This research also provides an optimal buy and sell plan that minimizes UT motor pool's total costs while satisfying all demand. The fleet size and composition optimization model is very flexible. It can be used for a wide variety of fleet optimization problems including fleet size and EV adoption as it was used here.

Although there has been a great deal of research examining carsharing and EVs independently, there is little research investigating how carsharing programs can adopt EVs efficiently. This process is impacted by different EV characteristics and specifications including costs, driving range, and charging infrastructure. The models from this study can guide a carsharing program's EV adoption in urban cities with well-developed public transit networks as readily as it can help vehicle fleets satisfy demands within cost constraints.

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APPENDICES

APPENDIX A: CARSHARING FEASIBILITY SURVEY FORM

车共用模式选择研究 (Carsharing mode choice study)

Part-1

Think back to yesterday.

Tell me about all trips you made.
(exclude link trip such as a walking trip from home to bus stop)

Ex> Distance from the Wudaokou station to Beijing Language and Culture University is 1.3 Km.

Part-2

If Carsharing is Launching in Beijing. They are New Energy Vehicles (plug-in electric car). It has same performance as gasoline car. It does not emit pollution from car, but from electric power plant.

The car looks like picture 1.

Suppose that Sunny, 20 °C, air quality is classified as Unhealthy.

You need extra 5 mins for access/egress time for carsharing.

What would you choose?

Part-3

All attributes are same as Part-2.

Now, suppose that you can use the carsharing for your whole daily trips from home.
(Origin – Destinations – Origin, Home-based)

The total travel time is same as Part-2.

The total costs (including fuel and parking) will be _____yuan for your trips (A)

What would you choose?

Origin *1= Home* *2=Work* *3=School* *4=Store* *5=Restaurant* *6=Entertainment* *7=Others*	**Destination** *1= Home* *2=Work* *3=School* *4=Store* *5=Restaurant* *6=Entertainment* *7=Others*	**Mode** *1= bus* *2= subway* *3= car (drive alone)* *4= car (passenger)* *5= ebike* *6= bike* *7= walk* *8= taxi* *9= motorbike* *10= others*	***Departure Time***	**Travel Time (Out of vehicle/ In-vehicle)**	**Trip Length** (*Km*)	**Trip Costs** (yuan) Include fare, tolls, parking, and fuel	**The number of Travelers with you**	**Travel time will be A**	**Travel cost will be A**	**Mode** *1-10 = Same as Part 1* *11 = carsharing*	**Mode** *1 = Same as Part 1* *2 = carsharing*
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		
								mins	RMB		

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公用汽车模式选择研究 (Carsharing mode choice study)　　Type32

第一部分

请您回想昨天：.

请您列出您昨天全天的出行过程。
(不包括去公交地铁站的出行，比如从家步行到最近的公交站点)

距离示例：从五道口地铁站到北京语言大学距离为 1.3 公里

起点	目的地	方式	出发时间	行程时间	出行距离 (公里)	出行花费 (元)	出行的总人数
1=家 2=工作地点 3=学校 4=商场 5=餐厅 6=娱乐场所 7=其他	1=家 2=工作地点 3=学校 4=商场 5=餐厅 6=娱乐场所 7=其他	1= 公交 2= 地铁 3=小汽车（自己开车） 4= 小汽车（搭乘） 5= 电动自动车 6= 自行车 7= 步行 8= 出租车 9= 摩托车 10= 其他		车外 / 车内时间 车外时间=取车+等待时间		包括车票费、过路费、停车费和燃油费	
				/			
				/			
				/			
				/			
				/			
				/			
				/			

第二部分

基家出行，起点-目的地-起点

如果“公用汽车”行动在北京开始启动，使用新型能源汽车（充电式汽车）

这辆车看起来像图片 1

假如今天天气是：雨天, 30 °C, 空气质量分类为：良。

您只需要多花 10 分钟使用和归还“公用汽车”车辆。

如果您总出行花费（包括燃油和停车）是

____元 (F)

您的选择是？

出行方式
1-10 = *和第一部分相同* 11 = *“公用汽车”*

第三部分

所有情况和属性都和第二部分相同。

.

假设：您现在可以根据您个人意愿在任意一次出行中使用“公用汽车”车辆

您的选择是？

出行时间将是 A	出行花费将是 E	出行方式 *1 = 和第一部分相同* *2 =和第二部分相同* *3 = “公用汽车*
分钟	元	
分钟	元	
分钟	元	
分钟	元	
分钟	元	
分钟	元	
分钟	元	

公用汽车模式选择研究 (Carsharing mode choice study)

1) 年龄 ________

2) 性别
____ 男性
____ 女性

3) 个人月收入
____ 小于 2,000 元
____ 2,000 ~ 4,000 元
____ 4,000 ~ 6,000 元
____ 6,000 ~ 8,000 元
____ 8,000 ~ 10,000 元
____ 10,000 ~12,000 元
____ 大于 12,000 元

4) 完成的最高教育水平
____ 初中及以下
____ 高中或中专
____ 本科或者大专
____ 硕士及以上

5) 你家拥有汽车数量？
____

6)你是否居住在小区里面
____ 是 ____ 否

7-a) 您现在有驾照么？

有, ____ 有多少年了
____ 否 (我计划在未来 ___年内拿得驾照)
____ 否 (我没有准备拿驾照的计划)

7-b) 您会为了使用“公用汽车”车辆而去获得驾照么？（目前没有驾照的人回答）

____ 是 ____ 否

8-a) 一年内，您计划购买新车么？

____是
燃料：☐ 汽油, ☐ 柴油, ☐ 混合动力, ☐ 电动汽车, 其他_______
种类: ☐ 轿车, ☐ 面包车, ☐ SUV, 其他_______
____ 否

8-b) 如果已经有了“公用汽车”系统，您还会买新车么？（有计划购买新车的人回答）

____ 我将会使用“公用汽车”车辆，但依然会买新车，不过会推迟购买时间
____我将会使用“公用汽车”车辆，但是我仍然按照原计划购买新车
____ 我会使用“公用汽车”车辆，所以我不会买车
____ 我不会使用“公用汽车”车辆，我会购买新车

9) 以 0~10 分打分，您对环境的关心程度是：

0 1 2 3 4 5 6 7 8 9 10
(完全不关心) (非常关心)

10) 以 0~10 分打分，你认为北京现在（当下这个时刻）的空气质量的分数是：

0 1 2 3 4 5 6 7 8 9 10
(很差) (很好)

11) 以 0~10 分打分，你认为北京的停车环境的分数是：

0 1 2 3 4 5 6 7 8 9 10
(很差) (很好)

12) 以 0~10 分打分，您因为停车问题或者步行环境问题而避免在北京驾车出行的频率是：

0 1 2 3 4 5 6 7 8 9 10
(从未没有) (很频繁)

13)车牌单双号限行有没有影响到您昨天的驾车出行？

____ 是 ____ 否

调查员填写部分:

调查员姓名 ______________________________
出行者交通工具 ______________________________
调查日期和时间______________________________
调查地点 ______________区______________

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APPENDIX B: LOOK UP TABLES (TRAVEL TIME AND COST)

	A		B		C	D	E
	Peak-time (07:00-09:00) (17:00-19:00)	Non peak-time	Peak-time (07:00-09:00) (17:00-19:00)	Non peak-time			
1 公里	2 分钟	1 分钟	3 分钟	2 分钟	15 元	31 元	15 元
2 公里	5 分钟	3 分钟	6 分钟	4 分钟	16 元	32 元	18 元
3 公里	7 分钟	4 分钟	9 分钟	6 分钟	17 元	32 元	20 元
4 公里	10 分钟	5 分钟	12 分钟	8 分钟	18 元	33 元	22 元
5 公里	12 分钟	7 分钟	15 分钟	10 分钟	19 元	34 元	25 元
6 公里	14 分钟	8 分钟	18 分钟	12 分钟	20 元	35 元	27 元
7 公里	17 分钟	9 分钟	21 分钟	14 分钟	21 元	36 元	29 元
8 公里	19 分钟	11 分钟	24 分钟	16 分钟	21 元	36 元	31 元
9 公里	22 分钟	12 分钟	27 分钟	18 分钟	22 元	37 元	34 元
10 公里	24 分钟	13 分钟	30 分钟	20 分钟	23 元	38 元	36 元
11 公里	26 分钟	15 分钟	33 分钟	22 分钟	24 元	39 元	38 元
12 公里	29 分钟	16 分钟	36 分钟	24 分钟	25 元	40 元	41 元
13 公里	31 分钟	17 分钟	39 分钟	26 分钟	26 元	40 元	43 元
14 公里	34 分钟	19 分钟	42 分钟	28 分钟	27 元	41 元	45 元
15 公里	36 分钟	20 分钟	45 分钟	30 分钟	28 元	42 元	48 元
16 公里	38 分钟	21 分钟	48 分钟	32 分钟	29 元	43 元	50 元
17 公里	41 分钟	23 分钟	51 分钟	34 分钟	30 元	44 元	52 元
18 公里	43 分钟	24 分钟	54 分钟	36 分钟	31 元	44 元	54 元
19 公里	46 分钟	25 分钟	57 分钟	38 分钟	32 元	45 元	57 元
20 公里	48 分钟	27 分钟	60 分钟	40 分钟	33 元	46 元	59 元
21 公里	50 分钟	28 分钟	63 分钟	42 分钟	34 元	47 元	61 元
22 公里	53 分钟	29 分钟	66 分钟	44 分钟	35 元	48 元	64 元
23 公里	55 分钟	31 分钟	69 分钟	46 分钟	36 元	48 元	66 元
24 公里	58 分钟	32 分钟	72 分钟	48 分钟	37 元	49 元	68 元
25 公里	60 分钟	33 分钟	75 分钟	50 分钟	38 元	50 元	71 元
26 公里	62 分钟	35 分钟	78 分钟	52 分钟	39 元	51 元	73 元
27 公里	65 分钟	36 分钟	81 分钟	54 分钟	40 元	52 元	75 元
28 公里	67 分钟	37 分钟	84 分钟	56 分钟	41 元	52 元	77 元
29 公里	70 分钟	39 分钟	87 分钟	58 分钟	42 元	53 元	80 元
30 公里	72 分钟	40 分钟	90 分钟	60 分钟	43 元	54 元	82 元
31 公里	74 分钟	41 分钟	93 分钟	62 分钟	44 元	55 元	84 元
32 公里	77 分钟	43 分钟	96 分钟	64 分钟	45 元	56 元	87 元
33 公里	79 分钟	44 分钟	99 分钟	66 分钟	45 元	56 元	89 元
34 公里	82 分钟	45 分钟	102 分钟	68 分钟	46 元	57 元	91 元
35 公里	84 分钟	47 分钟	105 分钟	70 分钟	47 元	58 元	93 元
36 公里	86 分钟	48 分钟	108 分钟	72 分钟	48 元	59 元	96 元
37 公里	89 分钟	49 分钟	111 分钟	74 分钟	49 元	60 元	98 元
38 公里	91 分钟	51 分钟	114 分钟	76 分钟	50 元	60 元	100 元
39 公里	94 分钟	52 分钟	117 分钟	78 分钟	51 元	61 元	103 元
40 公里	96 分钟	53 分钟	120 分钟	80 分钟	52 元	62 元	105 元

	1 小时	2 小时	3 小时	4 小时	5 小时	6 小时	7 小时	8 小时
F	12 元	24 元	36 元	48 元	60 元	72 元	84 元	96 元
G	15 元	30 元	45 元	60 元	75 元	90 元	105 元	120 元
H	18 元	36 元	54 元	72 元	90 元	108 元	126 元	144 元

APPENDIX C: SURVEY LOCATION

1. **Haidian Qu**
- Wudaokou Station
- Huaqingjiayuan Apartment
- Hualian Shopping Mall, Lotus Shopping Mall
- Tsinghua University
- Beijing Language and Culture University

2. **Xicheng Qu**
- National Museum parking lot near the Tiananmen subway station
- Xidan station shopping mall and parking lot
- Xizhimen station shopping mall and parking lot

3. **Dongcheng Qu**
- Beijing Hotel parking lot near the the Wang Fu Jing subway station
- Dongzimen station shopping mall and parking lot
- Dongdan station shopping mall and parking lot

4. **Xuanwu Qu**
- Railway Building parking lot near the Military Museum subway station

5. **Chongwen Qu**
- Tian Tan Park parking lot near the Tian Tan East Gate subway station

6. **Chaoyang Qu**
- National Aquatics Center parking lot near the the Olympic Park subway station
- Apartment complex

7. **Fengtai Qu**
- Fengtai railway station
- Apartment complex

VITA

Taekwan Yoon was born on February 4, 1981, and grew up in Seoul, Republic of Korea. Taekwan switched his career from environmental and biotechnology to transportation engineering in 2006 at Seoul National University as a Master's student. After completing his Master's degree in City Planning (Transportation), he studied at Ohio State University, Columbus, OH in 2008 as a graduate student. He left the school in 2009 and returned to Korea to work at Korea Institute of Construction Technology as a Research Associate for 2 years.

In 2011, Taekwan took a position as a graduate research and teaching assistant at the University of Tennessee, Knoxville and started research projects such as carsharing feasibility study, electric vehicle fleet size and composition optimization, and the first shared electric bicycle program (cycleUshare) in North America. During summer 2013, he had the opportunity to study carsharing feasibility and potential demand in Beijing as a visiting scholar at School of Environment, Tsinghua University, Beijing, China.

During his Ph.D. study, he was selected as the first place winner in the Southern District ITE paper competition, John Harper Memorial Scholarship recipient, Korean-American Scientists and Engineers Association-The Korea-US Science Cooperation Center Graduate Scholarship recipient, and US-Korea Conference 2013 poster award. He was also honored with the Certificate of Appreciation for Service to Knoxville Community and Honorary Citizen (twice) from The City of Knoxville, TN and the Appreciation Awards from the Federation of Korean Associations, Southeastern, USA and Consulate General of the Republic of Korea in Atlanta. His

research was featured in UTK's Civil Engineering Department and College of Engineering Newsletters multiple times.

Mr. Yoon is active in ITE and TRB activities and has served as a reviewer and editorial board for several academic journals. He also served as the president for Korean Graduate Student Association at the University of Tennessee, Knoxville for 2 years. Taekwan graduated with his Ph.D. in May 2014.