Western Michigan University
ScholarWorks at WMU

Transportation Research Center Reports

Transportation Research Center for Livable Communities

8-31-2016

15-08 Community-Aware Charging Station Network Design for Electrified Vehicles in Urban Areas: Reducing Congestion, Emissions, Improving Accessibility, and Promoting Walking, Bicycling, and use of Public Transportation

Ratna Babu Chinnam
Wayne State University, ratna.chinnam@wayne.edu

Alper E. Murat
Wayne State University, amurat@wayne.edu

Follow this and additional works at: https://scholarworks.wmich.edu/transportation-reports

 Part of the Transportation Engineering Commons

WMU ScholarWorks Citation

Chinnam, Ratna Babu and Murat, Alper E., "15-08 Community-Aware Charging Station Network Design for Electrified Vehicles in Urban Areas: Reducing Congestion, Emissions, Improving Accessibility, and Promoting Walking, Bicycling, and use of Public Transportation" (2016). *Transportation Research Center Reports*. 20.
https://scholarworks.wmich.edu/transportation-reports/20

This Report is brought to you for free and open access by the Transportation Research Center for Livable Communities at ScholarWorks at WMU. It has been accepted for inclusion in Transportation Research Center Reports by an authorized administrator of ScholarWorks at WMU. For more information, please contact wmu-scholarworks@wmich.edu.

TRCLC 15-08
August 31, 2016

Community-Aware Charging Station Network Design for Electrified Vehicles in Urban Areas:

Reducing Congestion, Emissions, Improving Accessibility, and Promoting Walking, Bicycling, and use of Public Transportation

FINAL REPORT

DEVELOPED BY:

Dr. Ratna Babu Chinnam (PI)
Professor
Tel: 313-577-4846; Fax: 313-578-5902
E-mail: ratna.chinnam@wayne.edu

Dr. Alper E. Murat (Co-PI)
Associate Professor
Tel: 313-577-4846; Fax: 313-578-5902
E-mail: amurat@wayne.edu

Transportation Research Center
for Livable Communities

Western Michigan University | University of Texas at Arlington | Utah State University | Wayne State University | Tennessee State University

Technical Report
Documentation Page

1. Report No. TRCLC 15-08	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle Community-Aware Charging Station Network Design for Electrified Vehicles in Urban Areas: *Reducing Congestion, Emissions, Improving Accessibility, and Promoting Walking, Bicycling, and use of Public Transportation*		**5. Report Date** August 31, 2016 **6. Performing Organization Code** N/A
7. Author(s) Dr. Ratna Babu Chinnam (PI), Dr. Alper E. Murat (Co-PI)		**8. Performing Org. Report No.** N/A
9. Performing Organization Name and Address Western Michigan University 1903 West Michigan Avenue Kalamazoo, MI 49008		**10. Work Unit No. (TRAIS)** N/A **11. Contract No.** TRCLC 15-08
12. Sponsoring Agency Name and Address Transportation Research Center for Livable Communities (TRCLC) 1903 W. Michigan Ave., Kalamazoo, MI 49008-5316		**13. Type of Report & Period Covered** Final Report 9/1/2015 - 8/31/2016 **14. Sponsoring Agency Code** N/A
15. Supplementary Notes		

16. Abstract

A major challenge for achieving large-scale adoption of EVs is an accessible infrastructure for the communities. The societal benefits of large-scale adoption of EVs cannot be realized without adequate deployment of publicly accessible charging stations due to mutual dependence of EV sales and public infrastructure deployment. Such infrastructure deployment also presents a number of unique opportunities for promoting livability while helping to reduce the negative side-effects of transportation (e.g., congestion, emissions, and noise pollution). In this phase, we develop a modeling framework (MF) to consider various factors and their associated uncertainties for an optimal network design for electrified vehicles. The factors considered in the study include: state of charge, dwell time, Origin-Destination (OD) pair.

17. Key Words Electric Vehicles Network Design, Livability, Stochastic Model	**18. Distribution Statement** No restrictions.		
19. Security Classification - report Unclassified	**20. Security Classification - page** Unclassified	**21. No. of Pages**	**22. Price** N/A

Disclaimer

The contents of this report reflect the views of the authors, who are solely responsible for the facts and the accuracy of the information presented herein. This publication is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program, in the interest of information exchange. This report does not necessarily reflect the official views or policies of the U.S. government, or the Transportation Research Center for Livable Communities, who assume no liability for the contents or use thereof. This report does not represent standards, specifications, or regulations.

Acknowledgments

This research was funded by the US Department of Transportation through the Transportation Research Center for Livable Communities (TRCLC), a Tier 1 University Transportation Center at Western Michigan University. We also would like to acknowledge our collaborators: Ford Motor Company – Vehicle Electrification Group, Southeast Michigan Transportation Operations Center (SEMTOC), Southeast Michigan Council of Governments (SEMCOG), HERE – Formerly known as NAVTEQ, Traffic.com.

Community-Aware Charging Station Network Design for Electrified Vehicles in Urban Areas:

Reducing Congestion, Emissions, Improving Accessibility, and Promoting Walking, Bicycling, and use of Public Transportation

EXECUTIVE SUMMARY

We developed a set of tools to support effective planning of network design for charging stations for EVs in urban areas. Such infrastructure deployment also presents a number of unique opportunities for promoting livability while helping to reduce the negative side-effects of transportation (e.g., congestion and emissions).

Mile-stone #1: Developed methods for efficient estimation of various factors important for network design and understand the uncertainties associated with these factors. Real time data from various publicly available resources are considered for the estimation of the factors.

Mile-stone #2: Given the factors contributing to livability aspects and robust network design for electrified vehicles, formulated a two-stage stochastic programming model to for the network design of EVs for a community.

Mile-stone #3: Applied the developed stochastic model and performed computational experiments, and analyzed the usefulness of the model in terms of improvements in livability factors and accessibility of the given network.

The goal of the project is to provide series of tools for the city and governmental planning agencies to evaluate the factors important for network design of EVs and improve livability aspects for the communities. Shared the findings with SEMCOG and planning to pilot the methods in collaboration with a SE-MI city under a project extension.

Table of Contents

Abstract 6

Introduction 7

Overall Modeling Framework 9

Current Work 10

Literature Review 10

Network Design for Electrified Vehicles 13

Parameters and Uncertainties 15

State of Charge 16

Dwell Time 16

Weekday vs. Weekend 17

Preference for Charging Away from Home 18

EV Market Penetration 19

Willingness to Walk 20

Two –Stage Stochastic Model Formulation 23

Modeling Uncertainty – Sample Average Approximation 25

Case Study 26

Livability Assessment 29

Traffic Reduction 31

Emissions Reduction 31

Public Health Benefits 32

Conclusions 32

Results Dissemination 33

References 33

Figures

Figure 1: Overall modeling framework for improving community livability indices and adoption of EVs and charging stations. 9

Figure 2: Recharging probability as a function of state of charge at the time of arrival (Source: Brooker and Qin, 2015). 16

Figure 3: Average dwell time as a function of activity (Source: Brooker and Qin, 2015). 17

Figure 4: The expected breakdown of vehicle arrival percentages for weekdays (left) and weekends (right) (Sources: Brooker and Qin, 2015; and Krumm, 2012). 18

Figure 5: Cumulative 2010-2014 BEV market share (left) and PHEV market share (right) across the U.S. (Source: Vergis et al., 2015). 19

Figure 6: Distance decay function for walking trips to different destination types (Source: Yang et al., 2013). 22

Figure 7: The small network used in our analysis. Blue dots are the optimal locations of charging stations for cases of p = 2 (left) and p = 3 (right) when market shares 1% for BEV and 2% for PHEV. 28

Figure 8: The larger network used in our analysis. Blue dots are the optimal locations of charging stations for cases of p = 1 (left) and p = 2 (right) when market share is 2% for BEV and 5% for PHEV. 28

Abstract

Advantages of electric vehicles (EVs) include diversification of the transportation energy feedstock, reduction of greenhouse gas and other emissions, energy security, fuel economy, reduced operating costs, and reduced emissions leading to lesser air pollution levels. As a part of government's encouragement on vehicle electrification objectives, the major automobile companies of the world are being challenged to produce affordable EVs by governments and environmentally conscious consumers. Several companies have accepted the challenge, and more models of EVs (hybrid vehicles, plug-in hybrid vehicles, pure battery EVs) are being introduced every year around the world. A major challenge for achieving large-scale adoption of EVs is an accessible infrastructure for the communities. The societal benefits of large-scale adoption of EVs cannot be realized without adequate deployment of publicly accessible charging stations due to mutual dependence of EV sales and public infrastructure deployment. Such infrastructure deployment also presents a number of unique opportunities for promoting livability while helping to reduce the negative side-effects of transportation (e.g., congestion, emissions, and noise pollution). In this phase, we develop a modeling framework (MF) to consider various factors and their associated uncertainties for an optimal network design for electrified vehicles. The factors considered in the study include: state of charge – the available charge in batteries of EVs at a given point of time, dwell time – drivers' willingness on length of time to park their vehicles in a given parking location (for potential charging), Origin-Destination (OD) Pair – EV demand for a given origin-destination within a community and the change in pattern during a week, preferences - drivers' preferences regarding their willingness to use publically available charging stations besides charging at home. Apart from these factors, we also consider the uncertainties in EV market penetration in the future and driver's willingness to walk (some distance) from charging station to destination. We present a case study and computation experiments to quantity the usefulness of the proposed two-stage stochastic mathematical model for network design, and provide insights in terms of improvements in livability aspects like reduction of traffic and emission, and increment of public health benefits. The proposed research relates and contributes to the attainment of strategic goals of the U.S. Department of Transportation and the U.S. Department of Energy. It contributes to the fostering of livable communities by increasing the access to transportation with EVs, improves adoption of EVs, and provides increased transportation choice. It further contributes to environmental sustainability through reduced carbon footprint of transport. Lastly, it contributes to the economic competitiveness through increased transportation productivity and more efficient utilization of existing system resources.

Introduction

Sustainability and livability are concepts that are of great interest to policy makers and city planners. According to Victoria Transport Policy Institute, sustainability promotes a balance among economic, social and environmental goals of community, and livability refers to the subset of sustainability goals such as air and noise pollution prevention, human health, and community development that are directly related to the life of people in the community. Indeed, walkability is a livability objective that can promote quality of life within a community. However, promoting a walkable lifestyle needs a safe and enjoyable environment as well as the pedestrian infrastructure.

On the other hand, according to the Environmental Protection Agency, 50% to 90% of air pollution in urban areas comes from automobile emissions. The challenges of rising fuel cost and climate change along with the clean fuel of EVs are great incentivizing factors for adopting these vehicles which will bring air quality, traffic congestion reduction, public health enhancement and global warming benefits to the community. According to Berger et al. (2015), an EV that draws its power from U.S. electrical grid emits at least 30% less *CO2* than comparable gasoline or diesel-fueled vehicles.

Encouraging people to walk and bike is one way to improve public health condition (Guell et al. 2013). Walking and cycling also reduce traffic congestion and air/noise pollution. Health benefits of walking include reducing the risk of heart pressure, reducing blood pressure, managing weight and improving fitness. The Centers for Disease Control and Prevention (CDC) reports that more American people are putting their lives at risk by becoming sedentary and obese. The mean walking-trip length and duration in the U.S. is estimated to be 0.62 miles and 16 minutes in 2001, and 0.61 miles and 12 minutes in 2009 (Yang et al. 2013). In 2009, 27% of all trips were shorter than 1 mile in the U.S., but only 36% of those trips were made by walking or cycling (Beuhler et al. 2011). The 2012 American Community Survey data reveals that the rate of walking to work in the U.S. has decreased from 5.6% in 1980 to 2.8% between 2008 and 2012. However, there is a great difference between the U.S. and other Western countries in non-motorized travel. For example, 25% of daily trips are made by bicycle and 22% are made by walking in the Netherlands (Kuzmyak et al. 2012). According to the National Personal Transportation Survey, percentage of all urban trips that have been done by walking or biking decreased from 10% in 1977 to 6.3% in 1995, whereas, people in Netherlands walked or biked 7 times more than people in the U.S. in 1995 (Pucher et al., 2003). CDC has recently developed the Active Community Environments (ACE) programs to encourage people to walk and bike more through urban design and

transportation policies (Centers for Disease Prevention and Control, 2002).

The societal benefits of large-scale adoption of EVs cannot be realized without adequate deployment of publicly accessible charging stations due to mutual dependence of EV sales and public infrastructure deployment. Such infrastructure deployment also presents a number of unique opportunities for promoting livability while helping to reduce the negative side-effects of transportation (e.g., congestion and emissions). Access to charging infrastructure is also among the most important factors that can increase market penetration of EVs. To build such an infrastructure, city planners and policy makers need to know the number of charging stations that are required, the optimal locations that they should be installed, and recharging capacity at each station (Miralinaghi, 2012). An effective design of charging network will influence travel behavior of drivers and can also encourage them to walk to their final destinations.

Public charging refers to any charging location that is away from home and can be located in both public parking structures and gas stations. Public charging stations are more important to drivers that have not installed one in their home (Dong and Lin, 2012). Besides locating charging stations, capacity is an issue that must be taken into account since low capacity will increase waiting time of drivers to charge their vehicles or even discourage them to use public charging stations. In addition, driving behavior and charging pattern of EVs are among critical factors that can affect economic and environmental benefits of EV adoption. A study by University of Michigan estimates that a plug-in hybrid EV will emit 252 to 262$g\ CO2$ per mile driven in 2030 depending on the allocation method using baseline grids and charging methods, which means that EV adoption will not be helpful in GHG-reduction in short term but it will definitely reduce emissions in the long-run (Hofmeister, 2014).

Since drivers are used to refueling their vehicles at gas stations, installing charging stations at gas stations will fit into their refueling behavior. It will also help maintaining public infrastructure utilization. On the other hand, since drivers won't be able to spend long time in gas stations, fast charging stations have to be considered for these places whereas people usually tend to park their vehicles for long hours in parking lots, which make lower-rate charging stations more feasible for parking places. However, a high parking fee may reduce the chance of using charging stations in parking lots (Cai et al., 2014). According to the International Parking Institute (IPI), the desire for more livable and walkable community has become the most important societal change that is influencing parking industry (International Parking Institute, 2015).

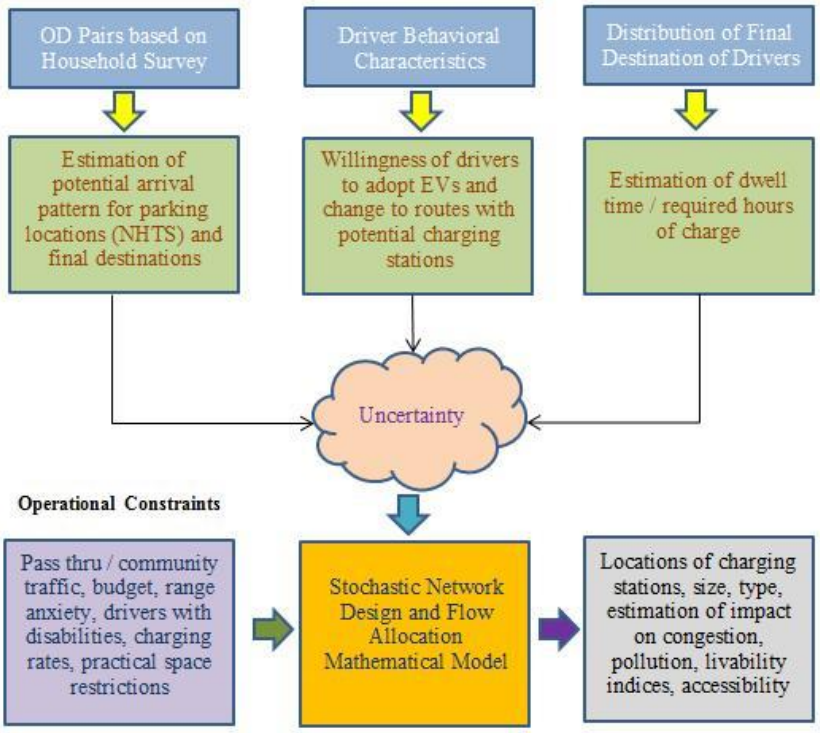


Figure 1: Overall modeling framework for improving community livability indices and adoption of EVs and charging stations.

Overall Modeling Framework

The aim of Phase 1 of the project is to develop methods, and eventually decision support tools, to aid planning agencies in promoting livability within communities through careful design of charging station networks for electrified vehicles (EVs). We have developed a stochastic mathematical optimization model to perform network design for EV charging stations while considering various aspects of livability for a community. The major components used for the stochastic model include: 1) OD traffic volume within a community, and the destination information includes parking location, and final destination (office, shopping, restaurant, hospital, etc.) of the drivers, 2) walking behavior of the drivers based on the demographics of a community and final destination of the drivers, 3) arrival pattern of EVs to parking locations, state of charge (SOC) and estimated dwell time, and 4) impact on congestion, pollution, charging rates and other livability indices.

The project uses data from National Household Travel Survey (NHTS), and extant studies about general walking behaviors/preferences of people. Based on the inputs from major components and user specified parameters from an analyst in a planning agency, the stochastic mathematical model

with an objective to maximize the livability indices and adoption of EVs proposes an optimal network for charging stations. Furthermore, pricing schemes are utilized to estimate the return on investments from the proposed network design in a post-optimization analysis.

Current Work

In the current Phase 1 part of this research, we want to develop models and methods to design an integrated framework for designing EV charging station network for a given region/community by determining number, location, and size of stations while explicitly accounting for the impact on traffic flows (reduced congestion), increased livability metrics (reduced noise, greenhouse emission, increased walkability), user choices (given, e.g., the range anxiety, trip distributions), as well as preferences of the charging station operators (cost of location, electricity, utilization and revenues).

Our model contributes to the fostering of livable communities by increasing the access to transportation with EVs, improves adoption of EVs, and provides increased transportation choice. It further contributes to environmental sustainability through reduced carbon footprint of transport. Lastly, it contributes to the economic competitiveness through increased transportation productivity and more efficient utilization of existing system resources. In addition, through the aim of reducing drivers walking commute to stations as well as their cost for charging, enables communities to be more livable for both the owners of EVs as well as general public by improving mobility, accessibility, and reducing congestion.

Literature Review

During the last decade, many researchers have focused on optimally locating alternative-fuel-vehicle's refueling stations. Some authors have studied the charging behavior of EV drivers. Lam et al. (2006) studied joint behavior of travel and parking of drivers through a time-dependent network equilibrium model. Their results showed that travel demand, walking distance, parking capacity and parking fee are the most important factors in determining parking behavior. Using driving pattern data in NHTS, Kelly et al. (2012) simulated PHEV charging and gasoline consumption. They analyzed the effects of charging location, charging rate, time of charging and battery size to measure the impact that PHEV adoption can have on energy consumption and emission reduction. Dong et al. (2012) examined the impact of public charging infrastructure on gasoline consumption of plug-in hybrid EVs. Their analysis showed that public charging infrastructure benefits PHEVs with small batteries the most and reduces energy consumption of PHEVs by 30% compared to charging stations installed at homes. Using battery EV charging data

in Japan, Sun et al. (2015) applied a mixed logit model to analyze the charging behavior of private and commercial battery EV drivers in terms of starting time of recharging. They found that state of charge, remaining time to the next travel and the distance that has to be driven in the next travel are the most important factors in deciding to charge the vehicle or not after the last trip of the day. Azadfar et al. (2015) studied the economic, environmental and technical factors that may affect charging behavior of EV drivers and in turn the electricity load on the grid. They found that charging infrastructure and battery performance are the most important factors in charging pattern of EV drivers.

Public health and transportation researchers tend to analyze walking and bicycling preference of people. Using travel survey data for the Minneapolis and St. Paul region of Minnesota, Iacono et al. (2008) estimated distance decay function for different travel modes, auto and non-auto modes, and several destination types in order to develop accessibility measures. While many studies have suggested 400 meters as the threshold for walking preference, their results showed that many pedestrians travel more than this threshold. Guell et al. (2013) investigated factors that affect walking and cycling to and from work in environments that are not supportive for these activities. Their analysis showed that one of the reasons that commuters decide to walk or bike to and from work in an unsupportive route is the availability of parking at work. Panter et al. (2013) examined the individual, workplace and environmental factors that could increase the share of walking and biking activities in travelling to and from work. They found that people who do not have access to parking at work and who have the most supportive environment are more likely willing to walk and bike. They suggested that providing limited or non-free parking at work and provide free off-site parking may encourage people to walk and bike more. Waerden et al. (2015) studied the relationship between car drivers' willingness to walk from parking lots to their final destinations and four trip purposes (work, social, weekly activity and non-weekly activity) using multi-nominal regression analysis. Analysis of responses of more than 300 members of the Eindhoven University of Technology's University Parking Panel showed that frequency of car use and parking duration are the most important factors determining willingness to walk.

Many researchers have concentrated on developing optimal charging infrastructure for EVs. Upcharch et al. (2009) considered the capacity of charging stations in the flow refueling location model (FRLM) in order to maximize the vehicle-miles travelled. In this case, optimal solutions in FRLM might become suboptimal solutions. To deal with computational burden of generating combinations of locations capable of serving the round trip on each route, Capar et al. (2012) developed a mixed-binary-integer optimization model. They showed that large-scale cases of their proposed model can be solved within short period of time. Capar et al. (2013) presented a more

computationally efficient model for flow-refueling location model to provide insights for managerial concerns such as OD demand forecasting uncertainty, robustness of optimal locations in regard to vehicle driving ranges. Zhang et al. (2013) investigated the relationship between EV charging infrastructure requirements, plug-in EV operating cost and battery EV feasibility. They concluded that all charging infrastructures reduce operating cost of plug-in EV and sufficient public charging infrastructure is needed to satisfy battery EVs. Wang et al. (2013) proposed a mixed-integer programming method to model capacitated multiple-recharging-station-location problem considering budget constraint and vehicle routing behavior, and using the concepts of set coverage and maximum coverage.

Baouche et al. (2014) a proposed mathematical model to minimize total cost, consisting of travel cost from demand zones to charging locations and investment cost, and find the optimal locations of charging stations for EVs in an urban area considering p-dispersion constraint. Dong et al. (2014) applied a genetic algorithm to find the optimal locations of charging stations for EVs considering the daily travel activity and charging behavior constraints. Their study showed that installing public charging stations will significantly increase EV adoption. Ahn et al. (2015) proposed a model to estimate the required density of charging stations for EVs for urban areas. They selected a city in South Korea to perform their analysis and determine the optimal density of charging stations. Cavadas et al. (2015) proposed a mixed-integer programming model to locate slow-charging stations for EVs in an urban environment considering the possibility that there might be several stops by each driver during the day and he only charge his vehicle at one of these locations. Since there may not be enough budgets to build a sufficient number of charging stations or since the adoption rate of EVs might be low, Chung et al. (2015) proposed a multi-period optimization method, a forward-myopic method, and a backward-myopic method to plan for optimal locations of charging stations. Since tour-based network equilibrium model can precisely track the state of charge of the battery and also consider the dwell time at each destination, He et al. (2015) proposed such a model to optimally locate public charging stations for EVs considering recharging behavior of drivers. Hosseini et al. (2015) proposed a two-stage stochastic program to locate permanent and portable charging stations with and without considering stations capacities to maximize the served traffic flows. Huang et al. (2015) developed an integer programming formulation to minimize the lifetime cost of equipment, installations, and operations of charging stations for plug-in EVs at workplaces by considering different charging levels and demographics of employees. In order to maximize the amount of vehicle-miles-travelled for an electrified vehicle, Shahraki et al. (2015) proposed a mathematical model to select the optimal locations for

public charging stations considering vehicle travel patterns. They applied their model on taxis data over a three week period of time in Beijing, China. Viswanathan et al. (2016) took a computational science approach to determine the optimal locations for charging stations of EVs. In their study, they have considered existing traffic and driving behavior of EV drivers.

Network Design for Electrified Vehicles

Widespread adoption of EVs along with introduction of new EV models capable of traveling longer distances will result in a need for building community-aware network of charging stations. As the EV usage for daily commute increases, the consideration for the ability to recharge these vehicles away from base locations (i.e., residential locations) will become even more important. While significant portion of the EV users will have sufficient battery state of charge (SOC) to complete their commuting trip, there will be EV users that would need intermediate recharging at their destination locations (e.g., workplace).

Our Phase 1 research aims at developing and demonstrating (at the proof-of-concept level) a system for the design and deployment of the charging infrastructure in support of the increasing adoption of EVs to improve livability (reduced congestion, noise, improve walkability) in urban areas, help ease users range anxiety, reduce user costs (e.g., walking), and reduce infrastructure cost. Our goal is to develop analytical data-driven tools and demonstrate that strategically planned and incentivized deployment of charging stations in urban areas would lead to improved livability of these areas, and these benefits will continue to increase with increased adoption of the EVs.

In this research, we develop a stochastic programming model to determine optimal infrastructure of charging stations for a community. There are many uncertainties such as state of charge (SOC) at the time of arrival to a location, parking duration based on type of the activity, driver's preference in terms of charging away from home and distance to walk from charging station to final destination that have to be considered in determining the locations of charging stations. The presence of all these uncertainties makes deterministic optimization irrelevant. So, different scenarios for uncertain parameters are generated and a stochastic optimization model is developed to account for these uncertainties in order to locate the optimal places for installing EV charging stations that have high potential of utilization and encourage people to walk more in the community since accessibility to charging infrastructure for EVs is being considered a fundamental component of community livability.

Since EVs must be parked for several hours to be recharged, we consider some parking lots, public parking facilities as well as parking spaces at workplaces, shopping malls and so on, as possible

locations for installing charging stations based on urban plans. To determine the exact final destination of each EV driver, we randomly assign each driver to a final destination location (to compute final walking distance) based on a uniform probability distribution.

We assume that each charging station has multiple outlets so that multiple drivers can charge their vehicles using the same charging station at the same time. This will help more demand to be met than the case where only one station is installed in every location. We assume that all charging point terminal types are semi-rapid charging ones (level 2 of charging power) that are typically recommended for private and public parking lots and shopping malls, and provide 10 to 20 miles range per hour of charging. Further research is needed to find the best mix of charging levels for any region. The required EV charging infrastructure depends on many factors such as EV market penetration, government support and charging behavior of EV drivers (Global EV Outlook, 2013).

The cost of installing charging stations at each location will depend on types of charging stations, number of stations, parking fee and the traffic level in the area of that location. It also depends on the distance from the facility's electrical panel and labor costs (Idaho National Laboratory Report, 2015). Rocky Mountain Institute has estimated that the cost of installing a level 2 charging station for public use is between $3,000 and $8,000 per charger in a parking garage and between $5,000 and $14,000 at a curbside. While using fast-charging stations are not very common now but it is expected that there will be more demand for this charging type in the future. The cost of purchase and installation of such a charging station is almost between $30,000 and $80,000. The following table shows in detail the cost of installing these two charging type stations in public places (Agenbroad and Holland, 2014):

Table 1: Cost of installing public level 2 charging stations. (Source: Agenbroad and Holland, 2014)

	Parking Garage		Curbside	
Cost Category	Low Estimate	High Estimate	Low Estimate	High Estimate
Hardware	$1,500	$2,500	$1,500	$3,000
Electrician Materials	$210	$510	$150	$300
Electrician Labor	$1,240	$2,940	$800	$1,500
Other Materials	$50	$100	$50	$150
Other Labor	$250	$750	$2,500	$7,500
Mobilization	$250	$500	$250	$500
Permitting	$50	$200	$50	$200
Total	$3,550	$7,500	$5,300	$13,150

We assume that garages and multi-level parking lots have enough capacity to accommodate all

vehicles and all drivers park their cars in these places since it is difficult to track walking distances to final destinations in case on-street parking is also considered. According to the literature, factors such as walking distance from parking lot to final destination, type of parking facility (e.g., underground parking, multilayer parking, curb parking, and off-road parking), parking fee, available parking spaces, trip purpose, search time, parking duration and access time to the parking place can significantly affect driver's decision to choose a parking place. However like Ji et al. (2007), we only consider walking distance to final destination the contributing factor in choosing a parking lot. In this study, we made the assumption that other factors such as safety, pedestrian facilities and enjoyable elements are in good shape and will not discourage people to walk from parking lots to their final destinations.

In order to make a balance between the utilization levels of charging service locations and alleviate congestion in certain points of the community, we need to put more charging stations in areas that have low normal congestion regardless of the number of EVs expected to frequent the neighborhood. We can also put a bound on the traffic that can be attracted to every charging location in certain time intervals. Traffic calming will reduce crashes, air and noise pollution and make the community safer and more livable. It is expected that demand for public charging stations has a peak load in the morning so the model has to consider charging time management to make a balance in electricity load on the grid. This can also be controlled through dynamic pricing of charging service at different time intervals during each day. In the next section, the sources of the uncertainties are described in detail and next, the model formulation and the solution approach are specified.

Parameters and Uncertainties

To simulate the behavior of EV drivers, we use the analysis of two surveys that were done few years ago: the 2009 National Household Travel Survey that was conducted by American Federal Highway Administration through phone surveys from more than 150 thousand U.S. households and the 2008-2012 American Community Survey that is a statistical survey and is done by the U.S. Census Bureau.

The first step in developing a network of charging stations is estimating demand for vehicle charging during a weekday or weekend. Like facility location models, we assume that demand occurs at fixed points on a network. This demand will be attracted to different charging station locations based on their distance preference for walking toward their final destination. Different scenarios represent various levels of EV state of charge at the time of arrival, duration of the activity, time of the week, preference of drivers for charging at public stations, and willingness to walk due to demographic, urban level and seasonality factors.

The following uncertainties can affect demand for public charging stations.

State of Charge

While demand for EVs is increasing due to environment and economy related concerns, these vehicles have a limited capacity battery to charge and use. Many factors such as commuting distance, driver's behavior, traffic congestion and weather condition can affect the state of charge of an EV when it arrives at a final destination. We expect that lower state of charge be associated with higher chance of recharging the EV while it is parked. Analysis of two year U.S. data from January 2011 to December 2013 of charging events that occurred away from home show that Nissan Leaf drivers prefer to charge their vehicles before their state of charge drops to lower levels while Chevrolet Volt drivers tend to start recharging when there is a little charge in the battery since their vehicles rely on both an electric motor and an internal combustion engine (Brooker and Qin, 2015). Figure 1 compares the probability of recharging as a function state of charge at the beginning of recharging for Nissan Leaf and Chevrolet Volt.

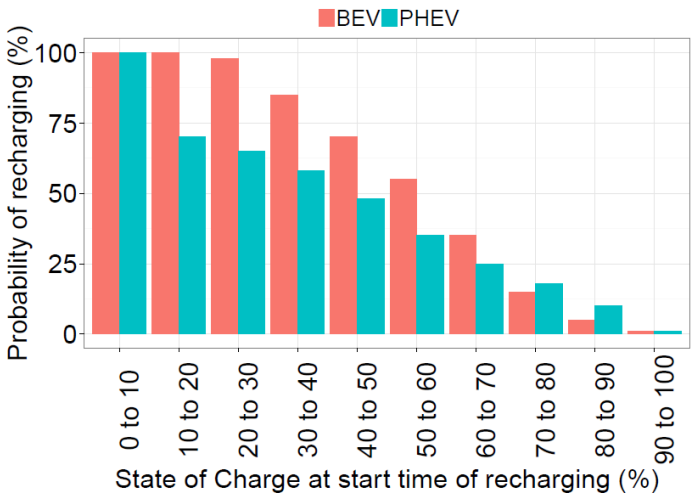


Figure 2: Recharging probability as a function of state of charge at the time of arrival (Source: Brooker and Qin, 2015).

As given in (MengTing et al., 2011; Luo et al., 2013; Fan et al., 2015) we assume that the initial state of charge distribution follows a normal distribution and it is set to be N(0.3; 0.1) in which the mean is 0.3 and standard variation is 0.1.

Dwell Time

To locate charging stations for EVs, we need to know how long each driver wants to park his car and that depends on the type of activity that any driver wants to do during his stay. The longer a

person wants to stay at her destination, the higher the chance that she tends to recharge her vehicle. We use six different destination categories that Brooker et al. (2015) defined based on NHTS data: Work, Social, Family, Meal, Study, and Shopping. Figure 2 shows how much time on average people tend to park their vehicles based on their trip purpose (Krumm, 2012).

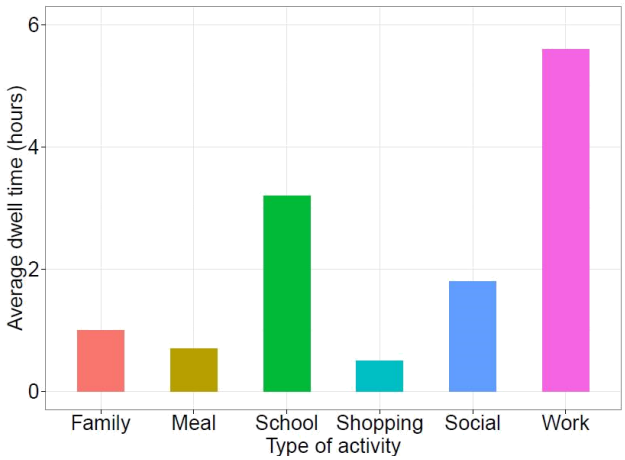


Figure 3: Average dwell time as a function of activity (Source: Brooker and Qin, 2015).

Zhong et al. (2008) concluded that Weibull, log-normal and log-logistic distributions are the best fitted distributions for modeling duration of activities on weekdays and weekends. While their analysis shows that model type and parameters or both might be different for an activity on weekdays versus weekends, they found Weibull distribution as the most applicable one among the three distributions. In addition, they found that certain activities such as social activities and shopping tend to last longer during weekend. So, we use Weibull distribution to estimate parking duration of EV drivers considering average staying time as in figure 2 for different activities. We also differentiated the duration of some activities like family outings, meal, school, shopping, social, and work in weekdays and weekends as described in next section.

Weekday vs. Weekend

People tend to attend social events, visit their families and go to shopping centers more during weekends than weekdays, in which demand mostly consists of people who are traveling for work or school so it is expected that a different demand pattern occurs for charging stations in different days of the week. Figure 3 confirms that demand for charging stations is dependent on time and type of day.

During weekdays, maximum demand (load) occurs during morning time when people are arriving at work or school but maximum demand usually happens around noon during weekends when people are going to shopping malls and social places. We use Weibull distribution for the arrival

time EVs to parking lots during weekdays and weekends based on the studies by Pashajavid et al. (2012) and Guner et al. (2015).

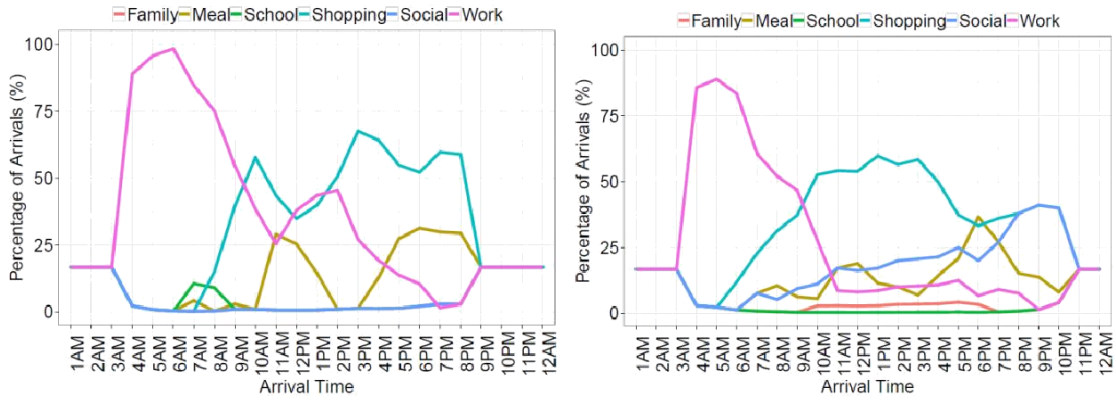


Figure 4: The expected breakdown of vehicle arrival percentages for weekdays (left) and weekends (right) (Sources: Brooker and Qin, 2015; and Krumm, 2012).

Preference for Charging Away from Home

Analysis of data collected by Idaho National Laboratory in 2012 and 2013 from over 4,000 Leafs and 1,800 Volts across the U.S. shows that drivers of Leaf prefer to charge away from home only 16% of the time and drivers of Volt prefer to do that in only 13% of the time. The data also shows that 13% of Leaf drivers and 5% of Volt drivers only charge their vehicles at home (Idaho National Laboratory Report, 2015). So vast majority of people intend to use publicly accessible charging stations.

Although the following table shows that many people that drive more daily miles tend to charge their vehicles in places other than their homes, the effect of daily miles travelled on the chance of charging away from home is small (Idaho National Laboratory Report, 2015):

Table 2: Travel daily mile and away-from-home charging behavior (Source: Idaho National Laboratory, 2015).

Tendency to charge away from home	Never	Sometimes	Frequently	Most of the time
Leaf average daily driving distance (mi)	25	31	43	32
Volt average daily driving distance in EV mode (mi)	25	29	40	26

EV Market Penetration

There are many social, environmental and economic factors that can significantly contribute to the increasing market share of different types of EVs. According to the U.S. Department of Energy, although the market share of batter EVs (BEVs) and plug-in hybrid EVs (PHEVs) are relatively high in some states, EVs are not very common in many states. Vergis et al. (2015) showed that the presence of charging infrastructure will contribute to the adoption of battery EVs but does not have any significant effect on the adoption of plug-in hybrid EVs. The following figures from the U.S. Department of Energy 2015 reports clearly show that BEVs and PHEVs have different market share across the states between 2010 and 2014.

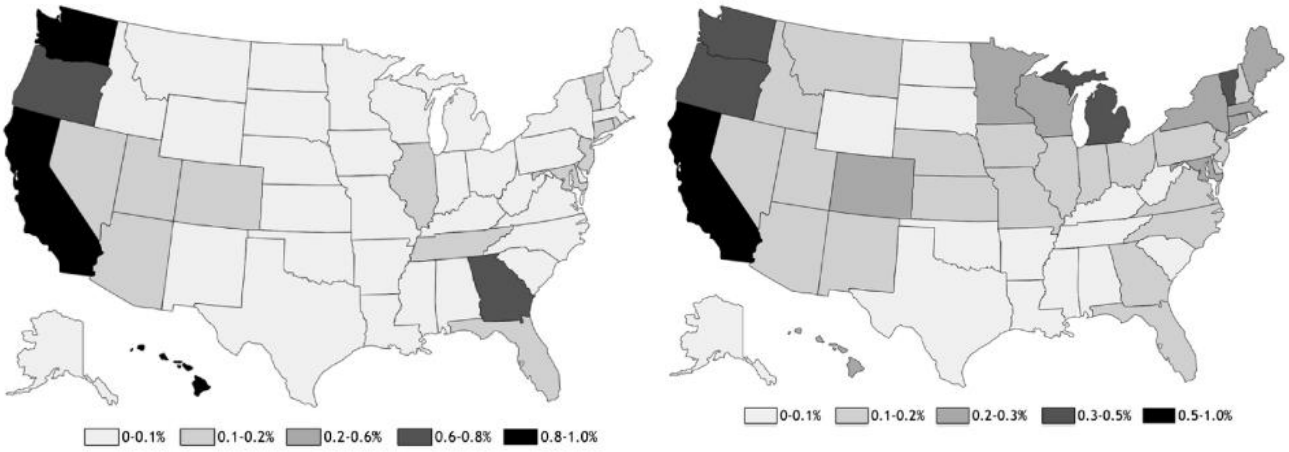


Figure 5: Cumulative 2010-2014 BEV market share (left) and PHEV market share (right) across the U.S. (Source: Vergis et al., 2015).

According to Turrentine et al. (2015), plug-in EV sales account for 0.6% of the 2015 U.S. market share. They believe that transition to EVs will take place like the market transition of hybrid cars and expected 3-5% of the market between 2015 and 2020, and 6-15% of the market between 2020

and 2025 will belong to electric cars. However, 2011 Energy Outlook report of the U.S. Department of Energy estimated the market share of EVs is less than 1% in 2035 while it projected that EV annual sales will be around 13,800 cars at that time.

Carley et al. (2013) surveyed adult drivers in large U.S. cities in fall 2011 in order to find factors that can affect their interest of buying a plug-in electric vehicle. Besides demographic variables that can strongly predict intent of purchase, their results show that the presence of a charging station inside the community is the only awareness variable that has a significant effect on intent of purchase. From policy point of view, one effective way to increase EV adoption is to build more charging infrastructure. Using multiple linear regression, Sierzchula et al. (2014) examined the effect of consumer financial incentives and several socio-economic factors on national EV market shares of 30 countries for the year 2012. While their descriptive analysis shows that neither financial incentives nor charging infrastructure contributes to adoption of EVs, statistical analysis confirms that installing one charging station (per 100,000 residents) could have twice the impact on a country's rate of new EV sales compared to$1,000 in financial incentives.

In fact, there is a chicken-and-egg problem between charging stations and EVs. Drivers want to make sure that there are enough charging stations before they buy any electric car and EV installers want to be sure that there is enough demand in the market for EVs before they start installing charging stations. Increasing charging infrastructure will help drivers not to get out of charge during daily travel.

Willingness to Walk

The willingness to walk of car drivers can be affected by their socio-demographic characteristics such as age, gender, education level, and occupation. Walking distances are shorter for children and elderly than young and middle-age groups. Past studies also show that walking preferences are correlated with many urban design factors such as street connectivity, pedestrian infrastructure and mixed land uses (Forsyth et al. 2008).

Fotheringham et al. (1989) proposed the unconstrained gravity model to predict the interactions between different urban zones.

$$T_{i,j} = K \times v_i^{\mu} \times w_j^{\alpha} \times c_{i,j}^{\beta} \quad (1)$$

In this model, $T_{i,j}$is the number of trips between zones i and j, v_i and $w_j$are the intensity of origin and destination zones, and $c_{i,j}$is the distance decay function component of the gravity model. This

function shows how an activity depends on the travel distance. For example, we expect that more people are willing to walk shorter distances than longer ones. By assuming that origins and destinations are known in the gravity model, this model reduces to the distance decay function part.

Many researchers have used distance decay function that shows the willingness to walk or bike a distance toward different types of destinations. The parameter of this decay function depends on the type of the final destination. Research using distance decay function has revealed different behaviors for people that live in different areas. For example, Icacano et al. (2008) found that people who live in Minnesota tend to walk and bike more for leisure and recreation purposes while Larsen et al. (2010) found that people would walk and bike longer distances for work than for other purposes in Montreal.

Estimation results of Yang et al. (2013) confirms that negative exponential distribution can better describe walking trips over short distances than distributions such as Gaussian. They specify the distance decay function as

$$P(d) = e^{-\beta \times d} \tag{2}$$

which shows the percentage of people that are willing to walk or longer distances. They used 2009 NHTS data to estimate the decay parameter for different groups and trip purposes. The estimated distributions for walking preference for different activities are shown in Figure 5.

Their analysis of the 2009 NHTS data shows that people are more willing to walk for recreation, social events and work activities rather than for studying, shopping, eating meal or dog-walking. Men also tend to walk farther than women but the difference is not significant. Adults between age 18 and 64 represent the highest rate of walking among age groups while old people and children tend to walk shorter distances.

There are many natural and built environment factors that can affect walking rates of people. The presence of hills and steep grades can influence walking negatively. Seasonal variations in weather such as hot summers and cold winters can prevent people to walk. Built environment characteristics such as mixed land use, urban design, neighborhood safety, city size, and community type can also make walking more attractive (Kuzmyak et al. 2012). Data show that the more compact the mixed land use is, the higher the chance that people tend to walk toward their final destinations. For example, American Community Survey displays that people living in cities walk more to work than in suburbs and outside metro areas.

In our study, we consider the effects of activity type, season, community size and U.S. region on the walking preference of people. Table 3 shows the variation for each of these factors based on walking distance preferences. Yang et al. (2013) estimated parameters for these distributions using2009 NHTS data.

The following estimations are also provided by Yang et al. (2013) using 2009 NHTS data for the walking distance preference of people in different regions, seasons and community size:



Figure 6: Distance decay function for walking trips to different destination types (Source: Yang et al., 2013).

Table 3: Estimated parameter for distance decay function for different factors and their categories (Source: Yang et al., 2013).

Factor	Category	β
Season	Winter (Dec-Feb)	1.88
	Spring (Mar-May)	1.68
	Summer (Jun-Aug)	1.64
	Autumn (Sep-Nov)	1.7
Region	Northeast	1.85
	Midwest	1.65
	South	1.76
	West	1.65
Community	Town and country	1.65
	Suburban	1.63
	Urban and second city	1.78

Two –Stage Stochastic Model Formulation

The following notations are used for the two-stage stochastic programming model:

- Sets
  - P: Set of parking lots.
  - S: Set of potential locations for charging stations.
  - L: Set of number of charging stations in each location.
  - Γ: Set of arrival times and departure times.
  - T: Set of times.
  - W: Set of scenarios.
- Fixed Model Parameters
  - p: Maximum number of locations that charging stations can be installed in.
- Scenario Dependent Parameters
  - $d_{\gamma(t),p,s}(w)$: Demand with arrival and departure time set of $\gamma(t)$ that is attracted from parking lot p to charging location s in scenario w.
  - $du_{s,s'}(w)$: Demand that can choose both locations s and $s'$for recharging in scenario w.
- First Stage Decision Variables
  - x_s: 1 if location s is considered for installing charging stations.
  - $z_{l,s}$: 1 if l charging stations are installed in location s.
- Second Stage Decision Variables
  - $y_{\gamma(t),p,s}(w)$: Captured demand with arrival and departure time set of $\gamma(t)$ that is attracted from parking lot p to charging location s in scenario w.

$c_{s,s'}(w)$: 1 if both location s and s' are chosen for installing charging stations

The two-stage stochastic optimization model is presented as follows:

First-Stage Model:

$$Max\ f(x,z) = E[\varphi(x,z,w)] \tag{3}$$

s.t

$$\sum_{s\in S} x_s = p \tag{4}$$

$$z_{l,s} \leq x_s \qquad l \in L, s \in S \tag{5}$$

$$\sum\nolimits_{l \in L, s \in S} z_{l,s} \leq 1 \tag{6}$$

$$x_s, z_{l,s} \in \{0,1\}, \qquad l \in L, \qquad s \in S \tag{7}$$

Second-Stage Model:

$$\varphi(x,w) = Max \sum\nolimits_{\gamma(t) \in \Gamma, p \in P, s \in S} y_{\gamma(t),p,s}(w) - \sum\nolimits_{s \in S, s' \in S} c_{s,s'}(w) \times du_{s,s'}(w) \tag{8}$$

$$\sum\nolimits_{\gamma(t) \in \Gamma, p \in P} y_{\gamma(t),p,s}(w) \leq \sum\nolimits_{l \in L} z_{l,s} \qquad s \in S, t \in T \tag{9}$$

$$y_{\gamma(t),p,s}(w) \leq d_{\gamma(t),p,s}(w) \qquad \gamma(t) \in \Gamma, p \in P, s \in S, t \in T \tag{10}$$

$$c_{s,s'}(w) \leq x_s \qquad s, s' \in S \tag{11}$$

$$c_{s,s'}(w) \leq x'_s \qquad s, s' \in S \tag{12}$$

$$c_{s,s'}(w) \geq x_s + x'_s - 1 \qquad s, s' \in S \tag{13}$$

$$c_{s,s'}(w) \in \{0,1\}, \; y_{\gamma(t),p,s}(w) \geq 0, \gamma(t) \in \Gamma, p \in P, s \in S, t \in T, w \in W \tag{14}$$

In this model, first-stage decisions are made on the locations of charging stations and subsequently, the decisions are exposed to uncertainties in the second-stage. In the second-stage, recourse decisions are made to maximize the potential traffic flows based on the locations chosen in the first-stage. Constraint 4 refers to the maximum number of locations that can be chosen for installing charging stations in the community. Constraints 5 and 6 determine the number of charging stations in any location that is selected for installing charging stations. Constraint 9 ensures that there is enough capacity to satisfy attracted demand to each station. Constraint 10 states that attracted demand cannot exceed the total possible demand at each time and station. Constraints (11) – (13) negate the sum of utilization of two individual charging stations when are located too close to each other. This represents cannibalization effect on demand when two charging stations are located too close.

Modeling Uncertainty – Sample Average Approximation

According to Santoso et al. (2005), a major difficulty in solving two-stage stochastic optimization problems is that we need to solve a huge number of linear optimization problems, one for each scenario, which makes the problem computationally intractable. We use sample average approximation (SAA) method to generate appropriate number of scenarios (within a prescribed confidence interval) to represent uncertainty for the two-stage stochastic programming model. Although our objective function is maximization, the following section represents a standard minimization problem.

The standard sample average approximation method is described as follows:

1. Estimating a lower bound for the optimal solution:

- Generate M independent sample sets of scenarios each of size N, i.e., $(w_j^1, w_j^2, \dots, w_j^N)$ for $j = 1,2, \dots, M$

- For each sample set m, find the optimal solution:

$$v_N^j = \frac{1}{N} \times \sum_{i=1}^{N} \varphi(x, z, w_j^i) \tag{15}$$

- Compute the followings:

$$\bar{v}_{N,M} = \frac{1}{M} \times \sum_{j=1}^{M} v_N^j \tag{17}$$

$$\sigma^2_{\bar{v}_{N,M}} = \frac{1}{M \times (M-1)} \times \sum_{j=1}^{M} (v_N^j - \bar{v}_{N,M})^2 \tag{18}$$

According to Norkin et al. (1998) and Mark et al. (1999) , the expected value of v_N is less than or equal to the optimal value v^* . Since the sample average $\bar{v}_{N,M}$ is an unbiased estimation of expected value of v_N, the $E[\bar{v}_{N,M}]$ is less than or equal to the optimal value v^*. So, $\bar{v}_{N,M}$ provides a lower statistical bound for the optimal solution.

2. Estimating an upper bound for the optimal solution:

- If $(\bar{x}, \bar{z})$ is a feasible solution for the first stage problem, we expect that $f(\bar{x}, \bar{z}) \geq v^*$. So, choosing any feasible solution of the first stage problem will provide an upper statistical bound for the optimal value.

- Choose a sample of size N' of scenarios, much larger than N, i.e., $(w^1, w^2, \dots, w^{N'})$ independent of samples to find the lower limit and estimate the objective function:

$$f(\bar{x}, \bar{z}) = \frac{1}{N'} \times \sum_{i=1}^{N'} \varphi(x, z, w^i) \quad (19)$$

$$f(\bar{x}, \bar{z}) = \frac{1}{N'} \times \sum_{i=1}^{N'} \varphi(x, z, w^i) \quad (19)$$

- Compute the variance for this estimation:

$$f(\bar{x}, \bar{z}) = \frac{1}{N'} \times \sum_{i=1}^{N'} \varphi(x, z, w^i) \quad (19)$$

3. Finding an estimation of the optimality gap:

- Use the upper bound and the lower bound that are computed in previous steps to find an estimation for the optimality gap:

$$gap_{M,N,N'}(\bar{x}, \bar{z}) = f(\bar{x}, \bar{z}) - \bar{v}_{N,M} \quad (20)$$

4. Checking the quality of the estimated optimality gap:

- an estimation for the variance of this estimated optimality gap can be found by

$$\sigma_g^2 ap = \sigma_{\bar{v}_{N,M}}^2 + \sigma_{N'}^2(\bar{x}, \bar{z}) \quad (21)$$

Case Study

To show the efficiency of the two-stage model, we have started conducting a variety of experiments using actual data obtained through SEMCOG for the Midtown area of Wayne State University in Detroit, MI. However, we are not yet done with these experiments. In the interim, we report here results from synthetic networks. In particular, we report here results from a small

test network and a larger network. The large network consists of 500 nodes as final destinations and 50 parking lots that drivers are already parking their vehicles. From these 50 parking lots, 10 are considered as potential locations for charging stations. In the small network case, 100 nodes are considered as final destinations. There are also 10 parking lots that drivers are already parking their vehicles from which 5 are considered as potential locations for charging stations. In addition, we assumed that we can install at most 2 packs of chargers with 4 outlets in small network and 2 packs of chargers with 10 outlets in large network in every possible location.

The following tables show the result of running the SAA for the small network problem in order to find the sufficient number of scenarios to get the optimal solution. This network is shown in figure 6. In these tables, average is the lower bound for the optimal solution, standard deviation is the standard deviation for this lower bound, gap is the difference between upper bound and lower bound for the optimal solution and sigma is the standard deviation for this gap.

Table 4: SAA result for case = 1 and (M,N′) = (20,1000).

N	Average	St. Dev.	gap	sigma
20	10.11	0.14	0.08	0.179
40	10.53	0.09	0.34	0.142
50	10.31	0.14	0.12	0.178

Table 5: SAA result for case = 2 and (M, N′) = (20,1000).

N	Average	St. Dev.	gap	sigma
20	20.7	0.25	0.09	0.335
40	21.03	0.24	0.42	0.328
50	21.03	0.22	0.42	0.314

Table 6: SAA result for case = 3 and (M,N′) = (20,1000).

N	Average	St. Dev.	gap	sigma
20	30.71	0.52	0.31	0.606
40	30.84	0.3	0.44	0.432
50	31.12	0.29	0.72	0.426

Table 7: SAA result for case = 4 and (M,N′) = (20, 1000).

	Average	St. Dev.	gap	Sigma
20	39.84	0.51	0.71	0.664
40	39.8	0.48	0.67	0.641
50	40.81	0.39	1.68	0.577

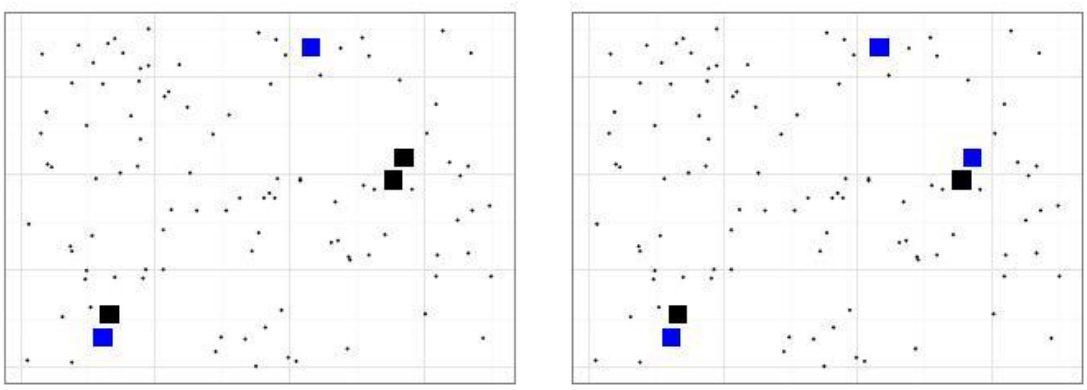


Figure 7: The small network used in our analysis. Blue dots are the optimal locations of charging stations for cases of p = 2 (left) and p = 3 (right) when market shares 1% for BEV and 2% for PHEV.

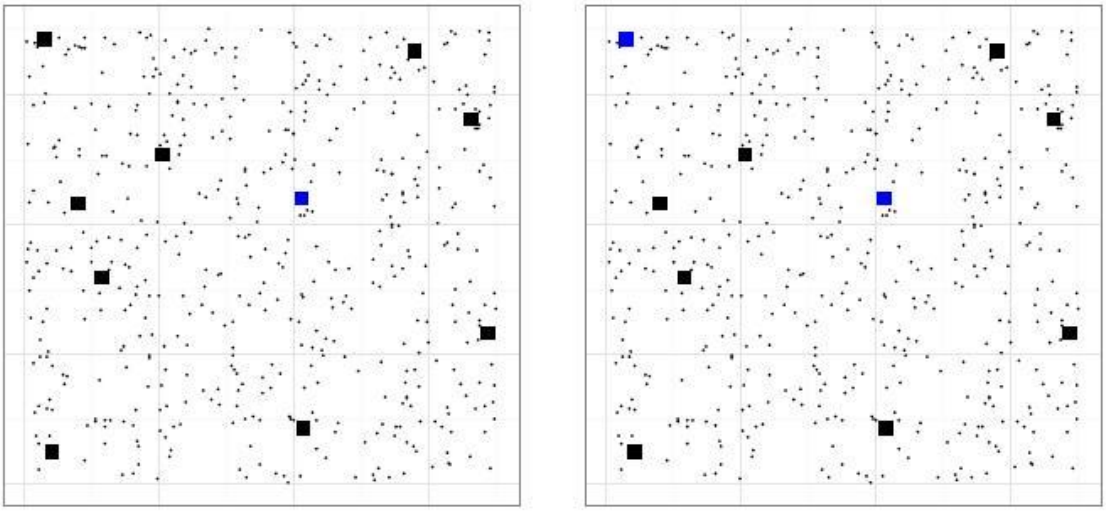


Figure 8: The larger network used in our analysis. Blue dots are the optimal locations of charging stations for cases of p = 1 (left) and p = 2 (right) when market share is 2% for BEV and 5% for PHEV.

The preliminary results of finding optimal locations for installing charging stations for small and large networks using Sample Average Approximation method are presented in figures 6 and 7, respectively. The smaller circle dots are showing the demand nodes and square dots are representing possible locations for installing charging stations. The optimal locations are shown in blue color. In these cases, we assume that total number of cars arriving to the community follows a uniform distribution between 2,000 and 4,000 per day in small network, and between 4,000 and 6,000 per day in large network.

Average of accessibility to charging stations and average of walking distances are computed for different scenarios of BEV and PHEV market shares in tables 8 and 9. Negative values for walking

imply that people are willing to walk less if we can install charging stations at the optimal locations. Average of accessibility to charging stations and average of walking distances are computed for different scenarios of BEV market share and PHEV market share and reported in Tables 8 and 9.

Livability Assessment

Developing a set of indicators is helpful in measuring the performance of transportation strategies that are designed to improve livability of the community. An important principle of livability analysis is increasing the transportation options for people so that they can meet at least a part of their travel needs through walking and biking. One example of performance measures is the percentage of trips that have been done through walking.

Table 8: Access to charging stations and walking distances in small network.

		Market Share: (BEV 1%, PHEV 2%)		Market Share: (BEV 0.05%, PHEV 0.4%)	
	Number of Chargers	Access	Walking distance	Access	Walking distance
$p = 1$	8	1%	16.99	1%	-14.74
$p = 2$	12	1%	17.29	1%	-5.6

Table 9: Access to charging stations and walking distances in large network.

		Market Share: (BEV 1%, PHEV 2%)		Market Share: (BEV 2%, PHEV 5%)	
	Number of Chargers	Access	Walking distance	Access	Walking distance
$p = 1$	10	1%	-34.73	1%	-54.71
$p = 2$	20	1%	-38.83	1%	-55.51

Some economists have measured in detail the benefits of walking and cycling. Litman (2009) estimated the external costs of walking and compared them to the ones of driving cars in average and peak urban conditions. He found that walking can save $0.25 per vehicle-mile and $0.50 per vehicle-mile travelled in average urban condition and urban-peak condition, respectively. The following table summarizes the monetized benefits of reduced motor vehicle travel per mile(Litman, 2016):

Table 10: Economic value of benefits of reduced motor vehicle travel per mile. (Source: Litman, 2016)

Impact	Urbane peak	Urban Off-Peak	Rural	Average
Congestion Restriction	$0.2	$0.05	$0.01	$0.06
Reduced Barrier	$0.1	$0.01	$0.01	$0.01
Energy Conservation	$0.03	$0.03	$0.03	$0.03
Pollution Reduction	$0.1	$0.05	$0.01	$0.044

The AARP Public Policy Institute has developed an index to measure livability in neighborhood level around the U.S. by focusing on old people since successful places to live usually are designed for elderly people. The institute surveyed 4,500 Americans of age 50 and above to come up with the following categories that determine a community's strengths and weaknesses (FHA 2011):

- Housing affordability as measured by housing cost burdens and the availability of subsidized housing
- Neighborhood quality as measured by safety metrics and vacancy rates, as well as proximity to grocery stores, parks, libraries jobs, and so on
- Alternative transportation options that connect people to social activities, economic opportunities and health care
- Environmental conditions, including air and water quality, as well as resiliency plans that incorporate disaster recovery and energy efficiency
- Health access, as measured by access to exercise options, health care availability, access to healthy food
- Civic engagement, including residents' ability to reduce social isolation through community engagement, measured by voting rates, number of cultural/arts institutions and organizations and access to the internet
- Employment opportunities

In this index, communities are compared against each other and get a score between 0 and 100 in each category. The average city gets 50 in each category and best places get 100. By studying the problem of finding the optimal locations for charging stations of EVs from sustainability point of view, Guo et al. (2015) developed and index system consisting of environmental, economic and social criteria to evaluate the performance of siting the optimal locations for EV charging infrastructure. Using research articles and feasibility reports of installing charging stations for EVs and judgment of the experts in the various fields such as environment, economy, society, electric

power system and transportation system, they came up with the following sub-criteria for selecting the optimal locations for charging stations:

Traffic Reduction

One way to improve neighborhood livability and encouraging people to walk is traffic calming and traffic reduction. While we want to attract drivers to charging stations that are within their walking preference distance, we want to avoid traffic increase in some locations during the peak time and divert them to other locations that have more unused parking spaces and less traffic flow. Grant-Muller and Laird (2007) and Litman (2009) estimated that traffic congestion of a motor vehicle on other road users costs $0.10 to $0.35 per mile during urban-peak hours. The traffic reduction can have the greatest effect on areas that schools and recreational centers exist. According to Litman (2009), per capita travel time and per capita congestion delay measure total congestion impact better than Level-of-Service (LOS) and Travel Time Index (TTI) since they consider shift in travel mode or change of destination.

Table 11: Criteria and sub-criteria for community livability analysis (Source: Guo et al.2015).

Criteria	Sub-criteria
Environment	Destruction degree on vegetation and water Waste discharge GHG emission reduction Fine particulate matter emission reduction
Economy	Construction cost Annual operation and maintenance cost Investment pay-back period
Society	Harmonization with the development planning of urban road network and power grid Traffic convenience Service capability Impact on people's lives

Emissions Reduction

Walking almost produces no pollution. According to the Pedestrian Bicycle Information Center, a research in Washington indicates that a 5 percent increase in walkability results in 5.6 percent fewer grams of nitrogen and 5.5 percent fewer grams of volatile organic compounds being emitted by vehicle travel. On the other hand, the level of emission from EVs depends on the type of power plants that are used to generate the required electricity for charging. Litman (2016) estimated that

the cost of pollution produced from driving automobiles is approximately 10 per mile for urban-peak, 5 for urban o -peak and 1 for rural areas.

Public Health Benefits

Many studies in the literature have shown that there is a positive relationship between physical activity and public health condition. According to WHO reports, physical inactivity contributes to 30% of ischaemic heart disease, 21-25% of breast and colon cancers, and 27% of diabetes incidents. The Centers for Disease Control and Prevention has initiated a Healthy People 2020 program that emphasizes on the increase of walking and cycling. The design of charging infrastructure can provide opportunities for people in a community to increase their level of physical activity. The New Zealand Transport Agency estimates that walking has a value of $3.7 2008 USD per mile for improving health and reducing congestion. The following table shows the monetized values of health benefits of walking provided by Land Transport New Zealand. These values are the combination of the benefits that each person can get from walking and the benefits that society can get (Litman, 2014).

Table 12: Economic value of public health benefits from walking (Source: Litman 2014).

Walking level	Internal Benefit ($)	External Benefit ($)	2007 U.S. Dollars per mile
Low	0.12	0.12	0.24
Medium	0.24	0.24	0.48
High	0.48	0.48	0.96

Conclusions

In this project, we studied and presented a two-stage stochastic programming model for network design of EV in a given community. The developed models and the resulting tools are expected to be used by planning agencies in the future. In continuation of the first phase, we expect to extend the study in a second phase. The second phase will enhance the modelling framework in following ways: a) identification of accessibility range for the community for the proposed EV stations network and include a minimum coverage requirement, and assess the impact of uncovered regions within a community, b) inclusion of multi-mode of transportation for a community and incentivize the potential EV charging stations based on their reachability for multi-modes of transportation, and gauge the shift in drivers' adoption of such EV charging stations, c) provision to quantify the

robustness and sensitivity of prescribed network design with respect to the changes in the arrival pattern, walking or adoption behavior of drivers and estimate the influence of pricing scheme on a network design; this will provide useful insights due to the randomness used for the model, and d) evaluation of the model with a pilot study for a community by partnering with a regional planning agency such as the SEMCOG.

Results Dissemination

Following are the plans for knowledge dissemination from this phase of the project:

- Optimization codes are developed using R and Python languages, and Gurobi was used as an optimization solver. The software codes will be packaged as modules and will be shared with planning agency (initially with SEMCOG) so they become part of their planning kit.
- The research with be presented in the upcoming conferences (INFORMS annual meeting to be held at Nashville in November).
- The study will be integrated in undergraduate and graduate courses (Courses - Introduction to Operations Research (UG) and Deterministic Optimization (PG)).

A manuscript has been prepared based on the current study and expected to be submitted by the end of summer. We are also preparing a white paper based on our case-study with SEMCOG and we intend to share the white-paper and possibly engage in training sessions with other national planning agencies.

References

[1] Emerging trends in parking, 2015. International Parking Institute.

[2] Huang, Y., Zhou, Y., 2015. An optimization framework for workplace charging strategies. Transportation Research Part C 52, 144-155.

[3] Sun, X., Yamamoto, T., Morikawa, T., 2015, Charge timing choice behavior of battery electric vehicle users. Transportation Research Part D 37, 97-107.

[4] Lam, W., Li, Z., Huang, H., Wong, S., 2006. Modeling time-dependent travel choice problems in road networks with multiple user classes and multiple parking facilities. Transportation Research Part B 40 (2006) 368-395.

[5] Azadfar, E., Sreeram, V., Harries, D., 2015. The investigation of the major factors

influencing plug-in electric vehicle driving patterns and charging behavior. Renewable and Sustainable Energy Reviews 42, 1065-1076.

[6] Kelly, J., MacDonald, J., Keoleian, G., 2012. Time-dependent plug-in hybrid electric vehicle charging based on national driving patterns and demographics. Applied Energy 94, 395-405.

[7] Dong, J., Lin, Z., 2012. Within-day recharge of plug-in hybrid electric vehicles: Energy impact of public charging infrastructure. Transportation Research Part D 17, 405-412.

[8] Cai, H., Jia, X., Chiu, A., Hu, X., Xu, M., 2014. Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet. Transportation Research Part D 33, 39-46.

[9] Guell, C., Panter, J., Ogilvie, D., 2013. Walking and cycling to work despite reporting an unsupportive environment: insights from a mixed-method exploration of counterintuitive findings. BMC Public Health, 13:497.

[10] Panter, J., Desousa, C., Ogilvie, D., 2013. Incorporating walking or cycling into car journeys to and from work: The role of individual, workplace and environmental characteristics. Preventive Medicine 56, 211-217.

[11] Larsen, J., El-Geneidy, A., Yasmin, F., 2010. Beyond the quarter mile: Re-examining travel distances by active transportation. Canadian Journal of Urban Research 19, 70-88.

[12] Iacono, M., Krizek, K., El-Geneidy, A., 2008. Access to destinations: How close is close enough? Estimating accurate distance decay functions for multiple modes and different purposes.

[13] Upchurch, C., Kuby, M., Lim, S., 2009. A model for location of capacitated alternative-fuel stations. Geographical Analysis 41, 85-106.

[14] Berger, D., Jorgensen, A., 2015. A comparison of carbon dioxide emissions from electric vehicles to emissions from internal combustion vehicles. Journal of Chemical Education 92, 1204-1208.

[15] Viswanathan, V., Zehe, D., Ivanchev, J., Pelzer, D., Knoll, A., Aydta, H., 2016. Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments. Journal of Computational Science 12, 1-10.

[16] Zhang, L., Brown, T., Samuelsen, S., 2013. Evaluation of charging infrastructure requirements and operating costs for plug-in electric vehicles. Journal of Power Sources 240, 515-524.

[17] Hofmeister, B., 2014. Electric vehicle charging infrastructure: Navigating choices regarding regulation, subsidy, and competition in a complex regulatory environment. Journal of Energy and Environmental Law, 42-71.

[18] Ahn Y., Yeo H., 2015. An analytical model to estimate the optimal density of charging stations for electric vehicles. PLoS ONE 10(11).

[19] Capar, I., Kuby, M., Leon, V., Tsai, Y., 2013. An arc cover path-cover formulation and strategic analysis of alternative-fuel station locations. European Journal of Operational Research 227, 142-151.

[20] Capar, I., Kuby, M., 2012. An efficient formulation of the flow refueling location model for alternative-fuel stations. IIE Transactions, 44:8, 622-636.

[21] Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transportation Research Part C 38, 44-55.

[22] He, F., Yin, Y., Zhou, J., 2015. Deploying public charging stations for electric vehicles on urban road networks. Transportation Research Part C 60, 227-240.

[23] Baouche, F., Billot, R., Trigui, R., El Faouzi, N., 2014. Efficient Allocation of Electric Vehicles Charging Stations: Optimization Model and Application to a Dense Urban Network. IEEE Intelligent transportation systems magazine 14, 33-43.

[24] Wang, Y., Lin, C., 2013. Locating multiple types of recharging stations for battery-powered electric vehicle transport. Transportation Research Part E 58, 76-87.

[25] Chung, S., Kwon, C., 2015. Multi-period planning for electric car charging station locations: A case of Korean Expressways. European Journal of Operational Research 242, 677-687.

[26] Shahraki, N., Cai, H., Turkay, M., Xu, M., 2015. Optimal locations of electric public charging stations using real world vehicle travel patterns. Transportation Research Part D 41, 165-176.

[27] Waerden, P., Timmermans, H., Bruin-Verhoeven, M., Car drivers' characteristics and the maximum walking distance between parking facility and final destination. The Journal of Transport and Land Use 1, 1-11.

[28] Forsyth, A., Hearst, M., Oakes, J., Schmitz, K., 2008. Design and destinations: Factors in u-encing walking and total physical activity. Urban Studies 45(9), 1973-1996.

[29] Centers for Disease Prevention and Control, Active Community Environments (Atlanta, Ga: National Center for Chronic Disease Prevention and Health Promotion, 2003). Available at: http://www.cdc.gov/nccdphp/dnpa/aces.htm. Accessed December 15, 2002.

[30] Pucher, J., Dijkstra, L., 2003. Promoting safe walking and cycling to improve public health: Lessons from the Netherlands and Germany. American Journal of Public Health Vol 93, No. 9, 1509-1516.

[31] Krumm, J., 2012. How people use their vehicles: Statistics from the 2009 National

Household Travel Survey. SAE International.

[32] Plugged in: How Americans charge their electric vehicles. Idaho National Laboratory.

[33] Kuzmyak, J., Dill, J., 2012. Walking and bicycling in the United States: The who, what, where and why. TR News.

[34] McKenzie, B., 2014. Modes less traveled-Bicycling and walking to work in the United States: 2008-2012. American Community Survey Reports.

[35] Fotheringham, A. S., O' Kelly, M., 1989. Spatial interaction models: formulations and applications. Boston: Kluwer.

[36] Yang, Y., Diez-Roux, A., 2012. Walking distance by trip purpose and population subgroups. American Journal of Preventive Medicine 43, 11-19.

[37] Brooker, R., Qin, N., 2015. Identification of potential locations of electric vehicle supply equipment. Journal of Power Sources 299, 76-84.

[38] Ji, Y., Deng, W., Wang, W. and Liu, G., 2007. Two-phased Parking Choice Model for Pre-trip Parking Guidance System, Proceedings of the 86th Annual Meeting of the Transportation Research Board, Washington DC, USA.

[39] Global EV outlook, Understanding the Electric Vehicle Landscape to 2020, 2013.

[40] Creating Livable Communities, How the transportation decision making process can support more livable community outcomes, Federal Highway Administration, 2011.

[41] Guo, S., Zhao, H., 2015. Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective. Applied Energy 158, 390-402.

[42] Hosseini, M., MirHassani, S., 2015. Refueling-station location problem under uncertainty. Transportation Research Part E 84, 101-116.

[43] Plugged In: How Americans charge their electric vehicles. 2015. Idaho National Laboratory.

[44] Becker, T., Sidhu, I., Tenderich, B., 2009. Electric vehicles in the United States: A new model with forecasts to 2030. Center for Entrepreneurship and Technology, University of California, Berkeley.

[45] Litman, T., 2009. Transportation cost and benefit analysis. Victoria Transport Policy Institute.

[46] Litman, T., 2014. Economic value of walkability. Victoria Transport Policy Institute.

[47] Vergis, S., Chen, B., 2015. Comparison of plug-in electric vehicle adoption in the United States: A state by state approach. Research in Transportation Economics 52, 56-64.

[48] Agenbroad, J., Holland, B, 2014. Pulling back the veil on EV charging station costs. Rocky Mountain Institute.

[49] Litman, T., 2016. Evaluating active transport benefits and costs. Victoria Transport Policy

Institute.

[50] Litman, T., 2015. Air pollution costs. Victoria Transport Policy Institute.

[51] U.S. Department of Energy, 2015. Fact of the Week 876, 877. Retrieved July 17, 2015 from: http://energy.gov/eere/vehicles/transportation-fact-week.

[52] Zhong, M., Hunt, J., Lu, X., 2008. Studying differences of household weekday and weekend activities: A duration perspective. Transportation Research Record 2054, 28-36.

[53] Turrentine, T., Kurani, K., Garas, D., Nicholas, M., Tal, G., 2015. Developing the plug-in electric vehicle market: World, USA California experience. UC Davis Plug-in Hybrid and Electric Vehicle Research Center.

[54] Electric vehicle market penetration: An examination of industry literature. The Texas Transportation Institute, Strategic Solutions Center.

[55] MengTing, D., JingHong, Z., Man, Z., WenZhuo, W., 2011. Optimization of electric vehicle charging capacity in a parking lot for reducing peak and filling valley in power grid. International Conference on Advanced Power System Automation and Protection.

[56] Luo, Z., Hu, Z., Song, Y., Xu, Z., Lu, H., 2013. Optimal coordination of plug-in electric vehicles in power grids with cost-benefit analysis |Part II: A case study in China. IEEE Transactions on Power Systems, Vol. 28, No. 4, 3556-3565.

[57] Fan, P., Sainbayar, B., Ren, S., 2015. Operation analysis of fast charging stations with energy demand control of electric vehicles. IEEE Transactions on Smart Grid, Vol. 6, No. 4, 1819-1826.

[57] Guner, S., Ozdemir, A., 2015. Distributed storage capacity modeling of EV parking lots. 9th International Conference on Electrical and Electronics Engineering (ELECO).

[58] Pashajavid, E., Golkar, M.A., 2012. Placing parking lot of plug-in electric vehicles within a distribution grid considering high penetration level of photovoltaic generation. Integration of Renewables into the Distribution Grid, CIRED workshop.

[59] Carley, S., Krause, R.M., Lane, B.W., Graham, J.D., 2013. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. Transportation Research Part D 18, 39-45.

[60] Sierzchula, W., Bakker, S., Maat, K., Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy 68, 183-194.

[61] Mock, P., Yang, Z., 2014. Driving electrification: A global comparison of fiscal incentive policy for electric vehicles. The International Council on Clean Transportation.