Life Cycle Analysis and Optimization of Wireless Charging Technology to Enhance Sustainability of Electric and Autonomous Vehicle Fleets

by

Zicheng Bi

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Natural Resources and Environment)
in the University of Michigan
2018

Doctoral Committee:

Professor Gregory A. Keoleian, Chair
Associate Research Scientist Tulga Ersal
Associate Professor Shelie A. Miller
Professor Michael R. Moore
Professor Kazuhiro Saitou

Zicheng Bi

bizc@umich.edu

ORCID iD: 0000-0002-6959-0526

DEDICATION

To my parents,

who gave me a love of life

To my wife Binxin,

who gave me a life of love

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my mentor Professor Greg Keoleian. You are a mentor who patiently teaches, a thinker who innovates, an “artist” who creates, a “gardener” who harvests, and a close friend who listens. It is truly a privilege to share a five-year journey in my life with you as my mentor and friend, who supports and encourages me regardless of ups and downs. You introduced me to this amazing venue of sustainability research as my career and shaped my views towards sustainable energy systems.

I would also like to thank my committee members, including Prof. Shelie Miller, Prof. Michael Moore, Prof. Kazu Saitou, and Dr. Tulga Ersal, for the helpful discussions and insightful feedback for me to complete and improve this dissertation.

I would like to acknowledge U.S. Department of Energy Clean Energy Research Center – Clean Vehicle Consortium, Argonne National Lab, University of Michigan Rackham Graduate School Pre-Doctoral Fellowship, and School for Environment and Sustainability for providing financial support.

I would also like to thank colleagues in Center for Sustainable Systems for their intellectual support, including Helaine Hunscher, Dr. Geoff Lewis, and Robb De Kleine. I am also grateful for Prof. Chris Mi (San Diego State University), Dr. Tianze Kan (San Diego State University), and Prof. Lingjun Song (Beihang University) for their expert support in my research.

Last but not least, I would like to express my sincere gratitude to my wife and soul mate, Binxin, for her unending love and unconditional support. Your love motivates me and keeps my momentum to work for a better life and a better world.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The transportation sector is undergoing a major transformation. Emerging technologies play indispensable roles in driving this mobility shift, including vehicle electrification, connection, and automation. Among them, wireless power transfer (WPT) technology, or commonly known as wireless charging technology, is in the spotlight in recent years for its applicability in charging electric vehicles (EVs). On one hand, WPT for EVs can solve some of the key challenges in EV development, by: (1) reducing range anxiety of EV owners by allowing "charging while driving"; and (2) downsizing the EV battery while still fulfilling the same trip distance. More en-route wireless charging opportunities result in battery downsizing, which reduces the high EV price and vehicle weight and improves fuel economy. On the other hand, WPT infrastructure deployment is expensive and resource-intensive, and results in significant economic, environmental, and energy burdens, which can offset these benefits.

This research aims to develop and apply a life cycle analysis and optimization framework to examine the role of wireless charging technology in driving sustainable mobility. This research highlights the technology trade-offs and bridges the gap between technology development and deployment by establishing an integrated life cycle assessment and life cycle cost (LCA-LCC) model framework to characterize and evaluate the economic, environmental, and energy performance of WPT EV systems vs. conventional plug-in charging EV systems. Life cycle optimization (LCO) techniques are used to improve the life cycle performance of WPT EV fleets. Based on case studies, this research draws observations and conditions under which wireless charging technology has potential to improve life cycle environmental, energy, and economic performance of electric vehicle fleets.

This study begins with developing LCA-LCC and LCO models to evaluate stationary wireless power transfer (SWPT) for transit bus systems. Based on a case study of Ann Arbor bus systems, the wirelessly charged battery can be downsized to 27–44% of a plug-in charged battery, resulting in vehicle lightweighting and fuel economy improvement in the use phase that cancels

out the burdens of large-scale infrastructure. Optimal siting strategies of WPT bus charging stations reduced life cycle costs, greenhouse gases (GHG), and energy by up to 13%, 8%, and 8%, respectively, compared to extreme cases of “no charger at any bus stop” and “chargers at every stop”.

Next, the LCA-LCC and LCO model framework is applied to evaluate the economic, energy, and environmental feasibility of dynamic wireless power transfer (DWPT) for charging passenger cars on highways and urban roadways. A case study of Washtenaw County indicates that optimal deployment of DWPT electrifying up to about 3% of total roadway lane-miles reduces life cycle GHG emissions and energy by up to 9.0% and 6.8%, respectively, and enables downsizing of the EV battery capacity by up to 48% compared to the non-DWPT scenarios and boosts EV market penetration to around 50% of all vehicles in 20 years.

Finally, synergies of WPT and autonomous driving technologies in enhancing sustainable mobility are demonstrated using the LCA framework. Compared to a plug-in charging battery electric vehicle system, a wireless charging and shared automated battery electric vehicle (W+SABEV) system will pay back GHG emission burdens of additional infrastructure deployment within 5 years if the wireless charging utility factor is above 19%.

CHAPTER 1

Introduction

1.1 Overview of wireless power transfer technology

The transportation sector is responsible for over 28% of energy use [1] and 27% of greenhouse gas (GHG) emissions [2] in the United States, mainly resulting from the combustion of petroleum fuels. Electric vehicles (EVs), including plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), are propelled by an efficient electric powertrain system which can be charged with electricity generated from renewable sources such as solar, hydro, and wind energy. Depending on the energy sources for charging, EVs offer opportunities to reduce worldwide energy use, GHG emissions, and criteria air pollutants [3] and enhance the sustainability of transportation systems.

Limited charging options and availability, however, became a major hurdle for accelerating vehicle electrification. Even though the global electric car stock increased almost six-fold from 2013 to 2016, the global electric car stock is currently only 0.2% of the total number of passenger light-duty vehicles in circulation [4].

Wireless power transfer (WPT) technology, or commonly known as wireless charging technology, offers a potential solution to the EV charging problems. A century ago, Nicola Tesla conducted experiments to transfer power wirelessly [5, 6]. In recent decades, WPT has been an area of intensive research to develop Tesla's prototype and improve the charging convenience of electric products in our lives. Typical examples include wireless charging cell phones, implanted medical devices, robots, home electronic appliances, as well as EVs. Unlike conventional plug-in charging technology for EVs, the wireless charging electric power is typically transferred via an electromagnetic field (EMF) in an air gap from the coil transmitters embedded in road pavement to the onboard coil receiver installed on the vehicle chassis [7-11]. This charging configuration no longer requires human intervention of plugging and unplugging the charging cables, which enables drivers to charge EVs in the following two modes: (1) stationary mode when EVs are parked or stopped above the wireless charging coil pads, often referred to as "stationary wireless charging" or stationary wireless power transfer (SWPT), and (2) dynamic mode when EVs are moving along a wireless charging lane on highways or urban roads, often referred to as "dynamic wireless charging" or dynamic wireless power transfer (DWPT). By enabling charging-while-driving for EVs, DWPT can help eliminate the "range anxiety" of EV drivers so as to boost the market adoption of EVs [12, 13]. The increasing demand for WPT stems from its inherent convenience and possibility of seamless operation without charging downtime that are otherwise two major problems for wired chargers. Therefore, WPT for EVs has the potential to overcome the drawbacks of wired chargers and eliminate some hurdles toward vehicle electrification and sustainable mobility.

Benefits of wireless charging in terms of energy, environmental, and economic metrics include:

- *Battery downsizing and vehicle lightweighting*. For example, wireless charging infrastructure has been constructed in Korea to charge electric buses [14-16] approaching bus stations to pick up and drop off passengers. Charging opportunities throughout the day-long bus operation would reduce the onboard battery size to one-third to one-fifth of the original battery, which usually comprises about a quarter of the weight of a bus [12, 17, 18]. Battery downsizing offers not only additional energy savings due to reduced vehicle weight, but also cost savings in terms of battery and use-phase electricity costs [17]. For passenger cars, a smaller battery is also possible when charging-while-driving becomes a reality. Although a downsized battery reduces the cost and production burdens and lightweights the vehicle, there is a trade-off of battery life versus battery capacity as reported in [19]. Therefore, battery life should also be incorporated when calculating battery life cycle burdens.
- *Boost EV market penetration*. Ubiquitous charging infrastructure enabled by dynamic WPT would theoretically allow EVs to have unconstrained range and a minimal capacity of onboard battery [20], and therefore the range anxiety of EV customers can be eliminated. Recent studies have predicted that DWPT would boost the EV sales share of light-duty vehicles from 2% in 2020 up to 70% in 2050, as compared to the business-as-usual case

with the EV sales share increasing from 2% in 2020 to 24% in 2050 [13]. The more DWPT road coverage, the more EVs would be expected in the market, thereby replacing conventional gasoline internal combustion engine (ICE) vehicles so that the energy savings and environmental benefits of EVs can be realized sooner.

- *More opportunities for charging renewable energy*. Electricity demand from wireless charging can be supplied by renewable energy such as solar panels deployed along the roadways as well as storage batteries for addressing solar intermittency, which offers emission-free electricity in the use phase. Therefore, DWPT offers another opportunity for charging with renewable energy and reducing use-phase emission and energy burdens.

Nevertheless, integration of WPT technology for EVs poses fundamentally unique challenges and burdens in terms of charging infrastructure deployment, and therefore there is a pressing need to develop robust and comprehensive frameworks to systematically evaluate the impacts and enhance the sustainability performance of WPT deployment, which is the focus of this dissertation. Despite the benefits of wireless charging, the challenges regarding the technology and its deployment include:

- *Large-scale charging infrastructure*. Charging-while-driving requires widespread coverage of DWPT infrastructure on major highways and urban roadways. Also, traffic intersections can be covered by SWPT when vehicles are waiting at traffic lights. This large-scale infrastructure would bring significant additional energy, environmental, and economic burdens associated with material production and energy consumption during the deployment phase.
- *Technical bottlenecks*. The grid-to-battery wireless charging efficiency is currently around 85% to 90% for SWPT and 72% to 83% for DWPT, as compared to 90% for plug-in charging [12]. There are also challenges in recognition of fast-moving WPT-EVs approaching charging lanes and real-time computation of electricity costs billed to the EV drivers. Other technical bottlenecks include the compatibility of DWPT and SWPT equipment, electromagnetic shielding, and detection and elimination of foreign objects in DWPT systems.

1.2 Research goals, novelties, and highlights

Research goals. From the sustainability perspective, wireless charging EV systems have the trade-off of large infrastructure deployment versus the benefits of battery downsizing and vehicle lightweighting in the use phase due to more in-route charging opportunities. Therefore, it is necessary to systematically assess the deployment and strategically optimize the siting of the charging infrastructure in order to minimize the life cycle burdens. Following overarching goals are established for this dissertation research:

a. Apply a life cycle analysis and optimization framework to examine the role of wireless charging technology in driving sustainable mobility.

b. By establishing the systems approach, highlight the trade-offs of stationary and dynamic wireless charging technology compared to plug-in charging technology in terms of infrastructure burdens and use phase savings.

c. Based on case studies, draw generalizable observations and conditions under which wireless charging technology has potential to improve life cycle environmental, energy, and economic performance of electric vehicle fleets.

d. Demonstrate the synergies of emerging technologies (wireless charging, shared mobility, autonomous driving, and battery electric vehicles) in enhancing sustainable mobility.

Research novelties. This dissertation fills the research gap by quantitatively characterizing the trade-offs and identifying sustainability challenges and opportunities for improving WPT EV system performance during their life cycles, including both public transit bus systems with stationary WPT and passenger car systems with both stationary and dynamic WPT. An integrated life cycle assessment (LCA) and life cycle cost (LCC) model is developed to provide a holistic view of technology deployment, encompassing not only the use-phase energy use, but also the burdens of infrastructure and equipment deployment necessary for the system. A comprehensive life cycle scope is important to objectively evaluate the emerging technology because wireless charging technology has trade-offs between infrastructure deployment burdens and use-phase benefits.

Research highlights. Moreover, the life cycle modeling framework is also integrated with optimization techniques to evaluate and improve the energy, environmental, and economic performance of electric transportation systems utilizing the emerging wireless charging technology, compared to the conventional plug-in charging technology. The modeled EV systems include: (1) urban transit buses, (2) passenger car networks on arterial roads, and (3) shared autonomous battery electric vehicle (SABEV) systems.

- For urban transit bus systems, discrete optimization using genetic algorithm is employed to select the bus stops as stationary wireless charging stations based on the bus dwell time at each stop and number of bus routes sharing each bus stop in order to improve the utility of charging infrastructure and minimize costs, GHG emissions, and energy during the life cycle of the fleet. Based on the case study of the University of Michigan bus routes, the optimal siting strategies can help reduce life cycle costs, GHG, and energy by up to 13%, 8%, and 8%, respectively, compared to conventional charging schemes.
- For passenger car systems, the arterial road networks in Washtenaw County in Michigan are used as a case study to demonstrate the economic, environmental, and energy feasibility of dynamic wireless charging technology for charging moving EVs on highways and urban roadways. Optimization using genetic algorithm techniques is used to select the ideal candidate road segments for wireless charging lane deployment based on the traffic volume, speed, and pavement condition according to transportation agency data (e.g., traffic counts and pavement remaining service life) [21, 22].
- For the SABEV systems, the synergies of the following technologies are demonstrated by a life cycle model calculating system payback time of GHG emissions from charging infrastructure production and deployment: (a) wireless charging technology; (b) shared mobility; (c) automated vehicles; and (d) battery electric vehicles. Results indicate that when the four technologies are deployed together and the wireless charging infrastructure is optimally deployed and highly utilized, the payback time of GHG emissions can be significantly reduced from more than 10 years to less than 5 years, compared to conventional mobility systems.

1.3 Overview of chapters

An overview of chapters is summarized in Table 1.1. Detailed description of each chapter is provided in the following sections.

Table 1.1 An overview of chapters

	Technology studied		Case study	Research aims	Impacts assessed
	SWPT	**DWPT**			
Chapter 1	(Introduction)				
Chapter 2	✓	✓	N/A	Identify the trade-offs, research gaps, challenges, and opportunities to enhance sustainability of wireless charging technology	N/A
Chapter 3	✓		Ann Arbor transit bus fleet	Compare the life cycle costs (LCC) of an electric transit bus system using wireless charging vs. plug-in charging, by integrating the LCC model with the life cycle assessment model	Life cycle costs, GHG* emissions, and energy
Chapter 4	✓		University of Michigan bus routes	Enhancing the life cycle performance of an electric transit bus fleet by optimizing the siting of wireless charging bus stops	Life cycle costs, GHG* emissions, and energy
Chapter 5	✓	✓	Washtenaw County arterial roads and passenger cars	Evaluate and enhance the life cycle performance of wireless charging technology for passenger car networks	Life cycle costs, GHG* emissions, and energy
Chapter 6	✓	✓	Shared autonomous and battery electric vehicle (SABEV) fleet	Evaluate the payback time of GHG* emissions of wireless charging infrastructure for an SABEV fleet, compared to a plug-in charging fleet, and demonstrate the synergies of wireless charging and SABEV to enhance sustainable mobility.	Life cycle GHG* emissions
Chapter 7	(Conclusions)				

Note: GHG = greenhouse gases; SWPT = stationary wireless power transfer; and DWPT = dynamic wireless power transfer.

This research has been (or would be) published in the following journal articles, and the following chapters are based on these publications:

- **Chapter 2**: Bi Z, Kan T, Mi CC, Zhang Y, Zhao Z, Keoleian GA. A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility. Appl Energ 2016;179:413-25. [12]
- **Chapter 3**: Bi Z, De Kleine R, Keoleian GA. Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system. J Ind Ecology 2016;21(2):344-55. [17]
- **Chapter 4**: Bi Z, Keoleian GA, Ersal T. Wireless charger deployment for an electric bus network: A multi-objective life cycle optimization. Appl Energ 2018;225:1090-101. [23]
- **Chapter 5**: Bi Z, Keoleian GA, Lin Z, Moore MR, Chen K, Song L, Zhao Z. Life cycle assessment and tempo-spatial optimization of deploying dynamic wireless charging technology for electric cars. Transport Res C (Under Review)

- **Chapter 6**: Enhancing sustainability of electrified mobility: Synergies of Wireless charging technology and Shared Autonomous Battery Electric Vehicles (W+SABEV) (Manuscript in preparation)

1.3.1 Chapter 2 - A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility

Research Question: *What are the challenges and opportunities surrounding wireless charging that influence the viability of this technology for future sustainable transportation?*

This chapter provides a comprehensive literature review that not only highlights the state-of-the-art technology development, but also identifies the opportunities and challenges for improving sustainability of WPT EVs. This review serves as a basis to guide research tasks of subsequent chapters.

The literature review encompasses the technical perspectives from leading research teams working on WPT technology development worldwide, in conjunction with the environmental and socio-economic perspectives that stem from the hands-on experience of practitioners working on deploying WPT-enabled EV systems. This chapter first highlights the technical aspects of both stationary and dynamic wireless charging systems. The chapter then evaluates case studies of real-world implementation and reviews the energy, environmental, economic, and societal impacts of WPT deployment, and provides insights to critically examine the role of WPT technology in the trend of advancing vehicle electrification and improving the sustainability of electrified mobility.

1.3.2 Chapter 3 - Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system

Research Questions:

- *What are the environmental, energy, and economic trade-offs of integrating stationary wireless charging in an electric transit bus system vs. the alternative plug-in charging technology?*
- *Under what conditions would wireless charging enhance the environmental, energy, and economic performance of electrified transit bus systems compared to plug-in charging?*

The research in this chapter aims to fill the knowledge gap of understanding the trade-offs of wireless charging technology from life cycle energy, environmental, and economic perspectives, by modeling a transit bus system in Ann Arbor as a case study. Through a comparative analysis of stationary wireless charging vs. plug-in charging for an all-electric bus system, this chapter highlights the battery downsizing and lightweighting benefits vs. the additional burden from wireless charging infrastructure deployment. The conditions under which wireless charging technology can have better life cycle performance are highlighted by a sensitivity analysis of key parameters. A scenario analysis is conducted to investigate the effect of battery recycling, carbon emission costs, and discount rate on the life cycle performance of wireless charging EV systems. An integrated LCA-LCC model framework has been developed to provide a comprehensive comparative assessment of plug-in charging vs. wireless charging with application for an electric bus fleet, as shown in Figure 1.1.

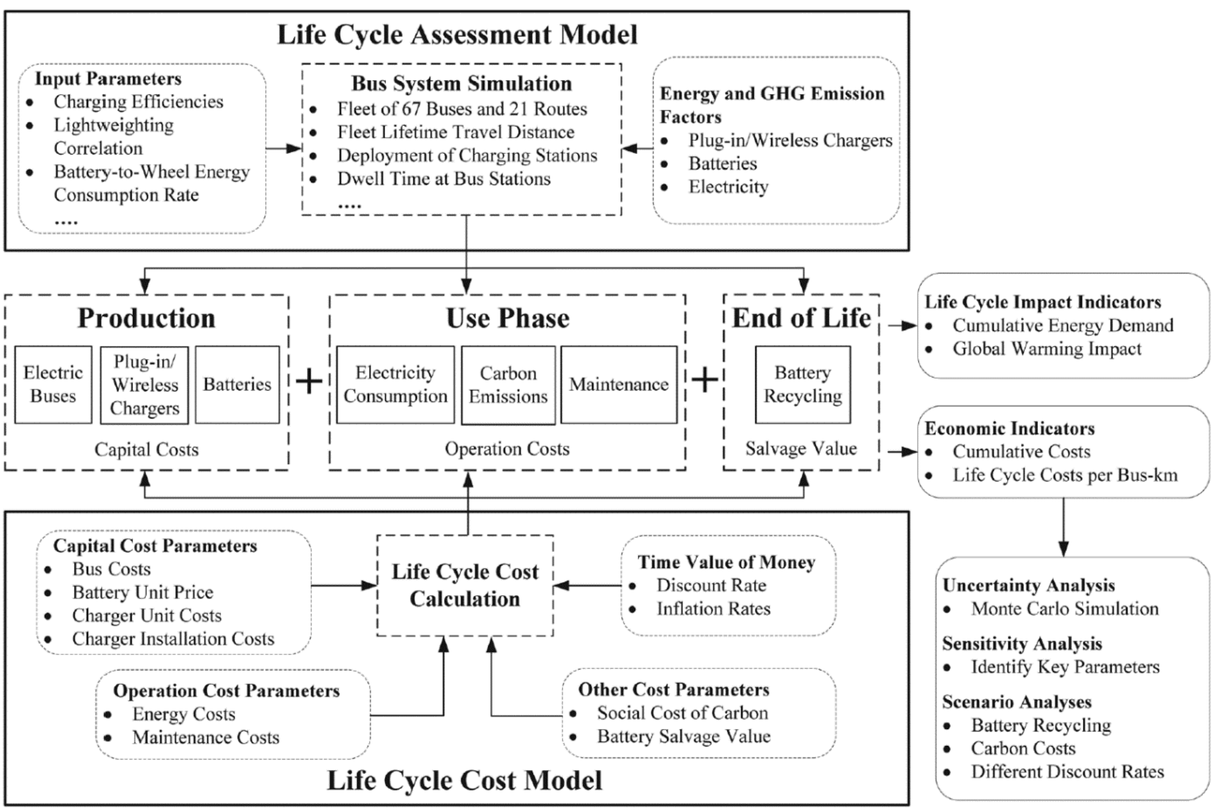


Figure 1.1 Integrated life cycle assessment and life cycle cost (LCA-LCC) model for comparative assessment of plug-in versus wireless charging systems with key parameters highlighted. The production of electric buses (excluding the batteries), use-phase maintenance, and battery recycling are only relevant to the LCC model

1.3.3 Chapter 4 - Wireless charger deployment for an electric bus network: A multi-objective life cycle optimization

Research Question: *How can wireless chargers be strategically sited at bus stops and batteries be sized while accounting for battery life, in order to minimize life cycle economic, environmental, and energy burdens?*

A multi-objective life cycle optimization framework is developed to enhance the economic, environmental, and energy performance of a wireless charging electric bus route network by strategically siting wireless chargers at bus stops and sizing battery capacity with a consideration of battery life.

Figure 1.2 shows the trade-offs of two extreme charger deployment cases, where “case 1” has no charger deployed en route while “case 2” has chargers deployed at every bus stop. The two cases are compared from the perspectives of infrastructure burden, battery burden, and use phase electricity burden. According to the comparison, “case 1” would require a smaller-scale charging infrastructure, larger battery capacity, and more use phase electricity consumption than “case 2”, and each specific state of charge (SOC) pattern has unique impacts on battery life. Apparently, these two cases are not optimal with respect to either cost or GHG emissions, so there must exist an optimal case where chargers are optimally sited and battery capacity is right-sized in order to achieve minimal life cycle burdens.

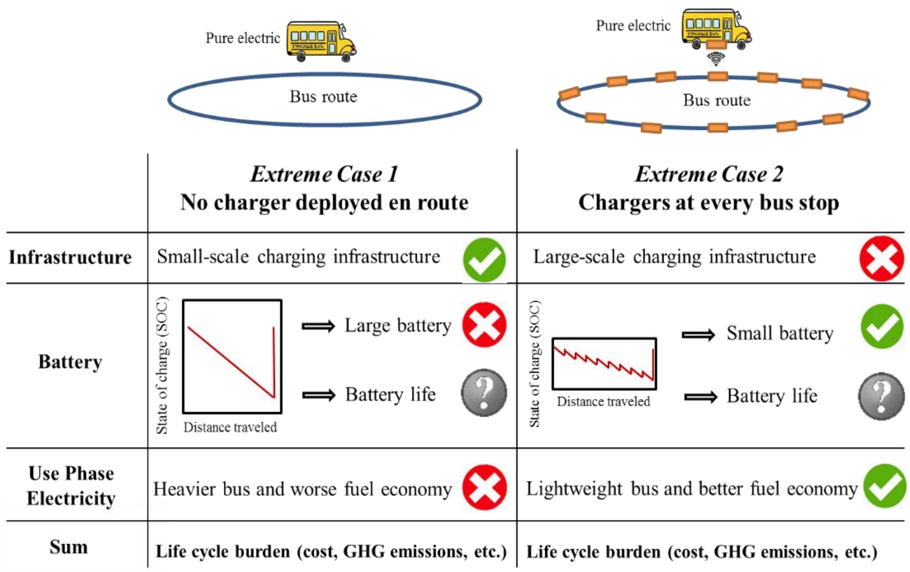


Figure 1.2 Trade-offs of a wireless charging all-electric transit bus route. The green check means a beneficial impact on life cycle burdens, and the cross in red indicates a negative impact on life cycle burdens

Given these trade-offs, a multi-objective life cycle optimization framework is established to strategically site the chargers and select battery capacity to minimize life cycle cost, GHG emissions, and energy. The model is based on the bus system operated by the University of Michigan. The charger siting considers the intersections of different routes and the utilization of each charger. The battery burden calculation considers the effect of SOC pattern on battery life [24]. The result indicates where the wireless chargers are best located and how large the battery should be in order to achieve the minimal life cycle cost, GHG emissions, and energy use.

1.3.4 Chapter 5 - Life cycle assessment and tempo-spatial optimization of deploying dynamic wireless charging technology for electric cars

Research Questions:

- *What are the economic, environmental, and energy trade-offs of integrating dynamic wireless charging for charging moving electric vehicles vs. the alternative plug-in charging technology and conventional gasoline vehicles?*

- *What are the optimal charging infrastructure deployment scenarios that minimize the life cycle economic, environmental, and energy burdens of the dynamic wireless charging vehicle systems?*

The life cycle model framework developed in previous chapters for stationary wireless charging electric buses is adapted and applied in this chapter for the assessment of dynamic wireless charging technology for charging electric cars in-motion. The study in this chapter develops a multi-objective life cycle optimization model that evaluates the economic, environmental, and energy performance of wireless charging EVs and wireless charging infrastructure systems from an LCA perspective. This study creates scenarios to understand under what conditions wireless-charging-based transportation systems could have better life cycle performance compared to plug-in charging systems in terms of costs, GHG, and energy. In addition, a detailed and comprehensive life cycle inventory analysis is conducted to quantify the life cycle primary energy, GHG emissions, and criteria pollutant emissions for the material production and manufacturing stages of dynamic wireless charging infrastructure and hardware devices.

A highlight of this LCA study is that the deployment of DWPT infrastructure is optimized both spatially and temporally. This study features not only the spatial optimization of DWPT charging lanes studied in literature [25, 26] showing that optimized deployment on key highways and urban roadways can electrify the majority of vehicle miles traveled (VMT) in a region, but also has a unique temporal optimization component for the gradual rollout of the DWPT infrastructure, which is usually overlooked in the literature. This optimization analysis aims to understand how to deploy DWPT considering spatial and temporal variations with objectives of minimizing life cycle costs, GHG, and energy:

- *Spatial optimization component*. This study studied the spatial optimization of DWPT charging lanes on highways and urban roadways, i.e., which road segments are selected for charging lane deployment. Three major characteristics or parameters of the roadway segments are considered: (1) traffic volume; (2) vehicle speed; and (3) remaining service life (RSL) of pavement, which quantitatively reflects the pavement condition. In general, a road segment with high volume, low speed, and poor condition is preferred for initial deployment as it will generate a high electrified VMT which means a high utilization rate of the deployed infrastructure, and also will reduce the burdens of charging lane deployment as it is more likely to deploy at the same time of scheduled pavement reconstruction and rehabilitation work.

- *Temporal optimization component*. This study also focuses on the temporal optimization of DWPT infrastructure rollout, i.e., in which year to deploy wireless charging lanes at each road segment. There are four major considerations: (1) EV sales; (2) costs of wireless charging infrastructure and battery; (3) wireless charging efficiency; and (4) battery downsizing. In general, DWPT deployment is good for boosting EV sales [13] more than business-as-usual so that the benefits of EVs can be realized sooner and it is also good for downsizing the battery and lightweighting the vehicle [18]. In contrast, later deployment is good when considering that DWPT and battery costs would both be cheaper and charging efficiency would be higher due to mass production and technology improvement. The market share of WPT-enabled hybrid EVs can be predicted from the given coverage rate of WPT infrastructure in a particular year, using the Market Acceptance of Advanced Automotive Technologies (MA3T) model developed by Oak Ridge National Lab [13].

In summary, the novel contribution of this study is the combined spatial and temporal optimization utilizing the holistic LCA scope to evaluate the performance of wireless charging under different scenarios and to provide guidance for DWPT deployment. The spatial optimization of selecting roadway segments considers traffic volume, speed, and pavement condition, and the temporal optimization of "when to deploy" considers cost reduction, technical improvement of wireless charging technology in the future, and EV market share growth as a function of DWPT coverage rate. To the best of authors' knowledge, it is also the first study using real-world traffic counts data for each segment of highways and urban roads [21] to evaluate life cycle performance of wireless charging technology deployment. The model is demonstrated using a case study of arterial roads in Washtenaw County in Michigan, USA.

1.3.5 Chapter 6 - Enhancing sustainability of electrified mobility: Synergies of Wireless charging technology and Shared Autonomous Battery Electric Vehicles (W+SABEV)

Research Question: *How much synergy will wireless charging technology bring when applied to a shared autonomous battery electric vehicle fleet in terms of payback time of GHG emissions from charging infrastructure, as compared with the baseline case with plug-in charging technology?*

This chapter synthesizes the insights from previous chapters and expands the research scope to investigate the synergies of the following four emerging technologies that have been growing rapidly in recent years for sustainable mobility:

- Wireless charging technology
- Shared mobility services (e.g., Uber and Lyft)
- Autonomous driving technology
- Battery electric vehicles

This work evaluates the synergies and trade-offs that wireless charging technology will bring to a shared autonomous battery electric vehicle (SABEV) fleet, by comparing a plug-in charging scenario to a wireless charging scenario. Previous research has demonstrated the opportunities in integrating autonomous vehicle technology into car sharing services and evaluated the fleet efficiency improvement benefits using an agent based modeling approach [27]. However, little research has evaluated the synergies of integrating both autonomous technology and wireless charging technology into a shared electric car fleet.

There are many pairs of synergies between these four emerging technologies. For example, autonomous vehicles provide strong synergy to accelerate the adoption of WPT technology by leveraging capabilities (such as charging alignment precision) to improve driving performance and wireless charging efficiency. For another example, wireless charging enables seamless operation which means there will be less charge downtime compared to plug-in charging, so that vehicles may operate more efficiently, resulting in the requirement of fewer number of vehicles serving the same passenger travel demand. However, the trade-off is that a larger scale infrastructure deployment is needed to ensure seamless operation.

The synergistic effect of autonomous driving technology integrated with wireless charging is evaluated using a case study of a wireless charging SABEV fleet in metropolitan areas. By comparing to the plug-in charging alternative, the benefits and trade-offs of coupling autonomous and wireless technologies are quantitatively characterized. The results indicate whether wireless charging will enhance the fleet performance in terms of reducing the payback time of GHG emissions from wireless charging infrastructure.

References

[1] Davis SC, Williams SE, Boundy RG. Transportation energy data book: Edition 35. Oak Ridge, Tennessee, USA: Oak Ridge National Laboratory; 2016.

[2] U.S. EPA. Inventory of U.S. greenhouse gas emissions and sinks: 1990-2015. Washington D.C., USA: U.S. Environmental Protection Agency; 2017.

[3] Hawkins TR, Gausen OM, Strømman AH. Environmental impacts of hybrid and electric vehicles—a review. Int J Life Cycle Ass 2012;17(8):997-1014.

[4] IEA. Global EV Outlook 2017. Paris, France: International Energy Agency (IEA); 2017.

[5] Tesla N. Art of transmitting electrical energy through the natural mediums. U.S. Patent 787412; April 18, 1905.

[6] Tesla N. Apparatus for transmitting electrical energy. U.S. Patent 1119732; December 1, 1914.

[7] Jang YJ. Survey of the operation and system study on wireless charging electric vehicle systems. Transport Res C 2018;In Press, https://doi.org/10.1016/j.trc.2018.04.006.

[8] Kan T, Nguyen T-D, White JC, Malhan RK, Mi C. A new integration method for an electric vehicle wireless charging system using LCC compensation topology: Analysis and design. IEEE Trans Power Electron 2016;PP(99):1-12.

[9] Onar OC, Miller JM, Campbell SL, Coomer C, White CP, Seiber LE. A novel wireless power transfer for in-motion EV/PHEV charging. In: 2013 twenty-eighth annual IEEE applied power electronics conference and exposition (APEC). IEEE; 2013. p. 3073-80.

[10] Zhang W, Mi CC. Compensation topologies of high-power wireless power transfer systems. IEEE Trans Veh Technol 2015;PP(99):1-10.

[11] Zhang Y, Zhao Z, Chen K. Frequency-splitting analysis of four-coil resonant wireless power transfer. IEEE Trans Ind Appl 2014;50(4):2436-45.

[12] Bi Z, Kan T, Mi CC, Zhang Y, Zhao Z, Keoleian GA. A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility. Appl Energ 2016;179:413-25.

[13] Lin Z, Li J, Dong J. Dynamic wireless power transfer: Potential impact on plug-in electric vehicle adoption. SAE Technical Paper 2014-01-1965; 2014.

[14] Choi SY, Gu BW, Jeong SY, Rim CT. Advances in wireless power transfer systems for roadway-powered electric vehicles. IEEE J Emerg Sel Topics Power Electron 2015;3(1):18-36.

[15] Suh IS. Intelligent wireless EV fast charging with SMFIR technology. J Integr Des Process Sci 2010;15(3):3-12.

[16] Suh IS, Gu Y. Application of shaped magnetic field in resonance (SMFIR) technology to future urban transportation. In: CIRP design conference 2011. 2011. p. 226-32.

[17] Bi Z, De Kleine R, Keoleian GA. Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system. J Ind Ecology 2016;21(2):344-55.

[18] Bi Z, Song L, De Kleine R, Mi C, Keoleian GA. Plug-in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. Appl Energ 2015;146:11–9.

[19] Jeong S, Jang YJ, Kum D, Lee MS. Charging automation for electric vehicles: Is a smaller battery good for the wireless charging electric vehicles? IEEE Trans Autom Sci Eng 2018;PP(99):1-12.

[20] Miller JM, Jones PT, Li J-M, Onar OC. ORNL experience and challenges facing dynamic wireless power charging of EV's. IEEE Circ Syst Mag: IEEE; 2015. p. 40-53.

[21] MDOT. Traffic Monitoring Information System (TMIS) by Michigan Department of Transportation (MDOT), https://mdotnetpublic.state.mi.us/tmispublic/; 2017 [accessed June 2017].

[22] MDOT. Pavement management system by Michigan Department of Transportation (MDOT), https://mdotcf.state.mi.us/public/tms/index.cfm?see=pave; 2017 [accessed May 2017].

[23] Bi Z, Keoleian GA, Ersal T. Wireless charger deployment for an electric bus network: A multi-objective life cycle optimization. Appl Energ 2018;225:1090-101.

[24] You S, Rasmussen CN. Generic modelling framework for economic analysis of battery systems. In: IET Conference on Renewable Power Generation (RPG 2011). IET; 2011. p. 1-6.

[25] Chen Z, He F, Yin Y. Optimal deployment of charging lanes for electric vehicles in transportation networks. Transport Res B 2016;91:344-65.

[26] Quinn JC, Limb BJ, Pantic Z, Barr P, Zane R. Techno-economic feasibly and environmental impact of wireless power transfer roadway electrification. In: 2015 IEEE wireless power transfer conference (WPTC). IEEE; 2015. p. 1-3.

[27] Fagnant DJ, Kockelman KM. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transport Res C 2014;40:1-13.

CHAPTER 2

A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility

Abstract

Wireless power transfer (WPT), which transmits power by an electromagnetic field across an intervening space, provides the prospect of new opportunities for electric vehicles (EVs) to enhance sustainable mobility. This review evaluates WPT technology for EV applications from both technical and sustainability perspectives. The objectives of this review include: (1) to present the state-of-the-art technical progress and research bottlenecks in WPT development and applications in the transportation sector; (2) to characterize the demonstrations of the real-world deployment of WPT EV systems; and (3) to evaluate the sustainable performance and identify challenges and opportunities for improvement. From the technical perspective, progress is reviewed with a focus on system performance. From the sustainability perspective, performance is defined in terms of energy, environmental, and economic metrics, and policy drivers and issues of health and safety are also examined.

2.1 Introduction

A century ago, Nicola Tesla conducted experiments to transfer power wirelessly [1, 2]. In recent decades, wireless power transfer (WPT) has been an area of intensive research to facilitate the penetration of electric products into our lives. Typical examples include wireless charging cell phones, electric vehicles (EVs), implanted medical devices, robots, and home electronic appliances. The power is typically transferred via an electromagnetic field (EMF). The widespread applications and increasing demand for WPT stems from its inherent convenience and possibility of seamless operation without charging downtime that are otherwise two major problems for wired chargers. Based on the working principles, WPT can be categorized as (1) electromagnetic radiation (microwave or laser) WPT that is applicable for long-distance power transmission, such as transmission between solar power satellites and the earth, (2) electric induction/coupling WPT (also known as capacitive coupling WPT) that is for near field transmission, and (3) magnetic coupling WPT (inductive or resonant) that is also for near field transmission but does much less harm to the human body than electric induction/coupling WPT due to the intensity of the electric field [3, 4]. Extensive work [3, 5-8] has been done on magnetic coupling WPT for EV charging applications, which is the focus of this review. In terms of working modes, WPT can be classified as either (1) static or stationary WPT: charge while the vehicle is not in motion; or (2) dynamic WPT: charge while the vehicle is moving along the WPT-enabled roadway.

WPT for EVs has the potential to overcome the drawbacks of wired chargers and eliminate some hurdles toward vehicle electrification and sustainable mobility [9]. Aside from its convenience compared to wired chargers, WPT can enable significant downsizing of the onboard EV battery. Take the stationary WPT for electric transit buses as an example where the onboard rechargeable battery can be downsized by at least two thirds [10, 11] due to the frequent "opportunity charges" while loading and unloading passengers at bus stations during bus operation. Attributable to these charges en route, it is reasonable to carry a much smaller onboard battery while still fulfilling the vehicle route requirements. This results in a substantial vehicle weight reduction given that the battery pack can comprise about a quarter of the weight of an all-electric transit bus for sustaining day-long operation [12]. Battery downsizing has significant implications for lightweighting the vehicle and improving the fuel economy [10]. In the scenario of dynamic WPT for passenger cars on major roadways, ubiquitous charging infrastructure would theoretically allow EVs to have unconstrained range and a minimal capacity of onboard battery [13]. Nevertheless, WPT for EVs poses additional sustainability trade-offs and concerns that have stimulated discussion in academia and industry. The trade-off is on the burden of large-scale WPT infrastructure deployment versus the benefits of battery downsizing and fuel economy improvement. The concern is on the technical and economic feasibility of dynamic WPT and the decrease in charging performance when the vehicle is moving at high speeds.

This chapter summarizes both the most up-to-date technical advances of WPT technology for EV applications and the state of sustainability assessments of WPT EV systems. It presents current research highlights, gaps, challenges, and opportunities of WPT technology for EVs from both the technical and sustainability perspectives. The chapter first introduces the fundamental theory of WPT and reviews the technical advances and challenges for both stationary and dynamic WPT. The second part highlights selected case studies of WPT applications. The third part summarizes the discussions on the sustainability, safety, and social implications of WPT technology, identifies challenges and opportunities for improving performance, and provides prospects to enhance sustainable mobility.

2.2 State-of-the-art research and technology development

Figure 2.1 shows a non-ionizing radiative wireless charging system for EVs through near-field magnetic coupling. The alternating current (AC) utility power first goes through the electromagnetic interface (EMI) stage, and then gets rectified and boosted to direct current (DC) power with a power factor of nearly 1.0 (0.95–0.98 in most cases), which is similar to a conductive charging system [14]. The voltage of the DC power is decreased by the BUCK stage. The BUCK stage can tune its output voltage to range from 0.03 to 0.97 of its input voltage, which achieves "soft" start/stop of the charger and continuous tuning of its output power. Here, the buck stage is optional since alternatively a pre-charge circuit, which is composed of two contactor relays and one resistor, is able to help achieve "soft" start of the charger and a phase-shift method can be used in the inverter stage to ensure the low power operation and "soft" stop of the charger. This combination of a pre-charge circuit and phase-shift method instead of a buck stage may reduce the system efficiency, but it will lower the total cost and volume of a wireless charging system. In the inverter stage, the DC power is converted to high frequency AC power, which then resonates in the primary compensation network and the primary coil, with the resonant frequency adjusted to the switching frequency of the inverter. The secondary coil receives the high frequency AC power wirelessly through the mutual inductance between the primary and secondary coils. The secondary compensation network, together with the secondary coil, is required to be tuned to have the same resonant frequency in order to maximize the transfer efficiency. The high frequency AC power is then rectified to DC power through the rectifier stage and filtered by the filter network. Finally, the DC power is available to charge the battery pack.

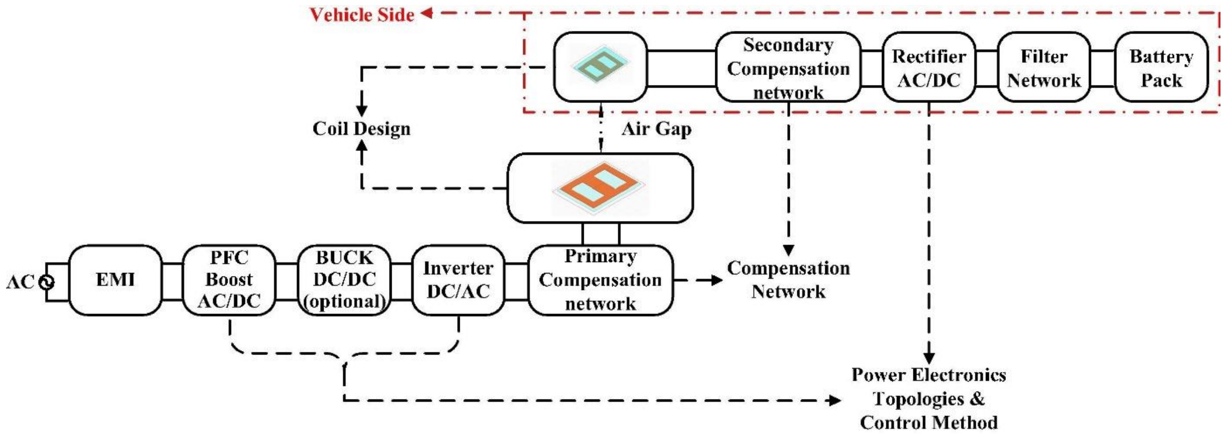


Figure 2.1 A non-ionizing radiative wireless charging system for electric vehicles. AC = alternating current; EMI = electromagnetic interface; PFC = power factor correction; DC = direct current

The coil is one of the most significant parts in a wireless charging system, for it converts energy between its electric form and its magnetic form, making WPT possible, while also determining the amount of power transferred and the system efficiency. In the literature, a coil system is generally classified as either a four-coil or a two-coil system. A four-coil system [15-17] offers the advantage of two degrees of freedom that the source coil can be mounted and coupled with the sending coil to adjust the system input impedance, and the load coil can be mounted and coupled with the receiving coil to adjust the equivalent load resistance seen from the receiving coil to match the load condition. A four-coil system is suitable for mid-range applications while a two-coil system gives better performance in short-range applications [18]. In [18], applications are considered short-range or mid-range based on whether the transmission distance is smaller or larger than the coil dimension. In EV applications, the transmission distance, also known as air gap, ranges typically from 100 mm to 300 mm [19], and the coil dimension is always larger than the transmission distance. Therefore, a two-coil system is preferable and will be reviewed in detail. In addition, ferrite bars or plates are always employed in coil systems to guide magnetic flux and provide magnetic shielding. Aluminum shields are often built into a coil system and serve as magnetic shields. Wireless charging systems for EVs are divided into stationary and dynamic charging systems, with each type having different coil designs.

2.2.1 Coil design for stationary charging systems

Basic coil systems for stationary charging systems are shown in Figure 2.2. Circular coil structures were studied and optimized in [20]. With the proposed coil structure, the system was able to transfer 2–5 kW wirelessly at a relatively high efficiency [20, 21]. However, the height of magnetic flux generated by the circular coil is limited. In order to solve this problem, [22] developed the solenoid coil structure, which improved the magnetic flux path. It was reported in [23] that a 3 kW wireless charging system using a solenoid coil structure was built and a DC-DC efficiency of 90% was achieved with an air gap of 200 mm. In addition, the solenoid coil structure performs well in wireless power transmission with a large air gap. [24] optimized the solenoid coil shapes and demonstrated a wireless charging system that delivered 1.403 kW power at an air gap of 3 m. The performance of the solenoid structure is fairly good, but there is a severe drawback. It generates double-sided flux and half of the flux is not used in transferring power. In addition, the unused flux may couple with the chassis of the vehicle and steel buried in the ground, which will greatly decrease the system efficiency. Therefore, this coil structure is not widely used in EV charging applications. In order to have a single-sided flux path and a larger charging zone than the circular coil structure, a bipolar coil structure known as a DD coil structure was developed in [25]. The bipolar coil structure shows excellent system efficiency at the desired power level with good tolerance to horizontal misalignment. [5] simulated the bipolar coil structure with the same size but different aspect ratios (ratio of width and length of a rectangular geometry). They built a wireless charging system employing the bipolar coil structure with the optimized aspect ratio to transfer 8 kW with a DC-DC efficiency of 95.66% at an air gap of 200 mm. Even when the horizontal misalignment increased to 300 mm, the system DC-DC efficiency was still as high as 95.39% [5].

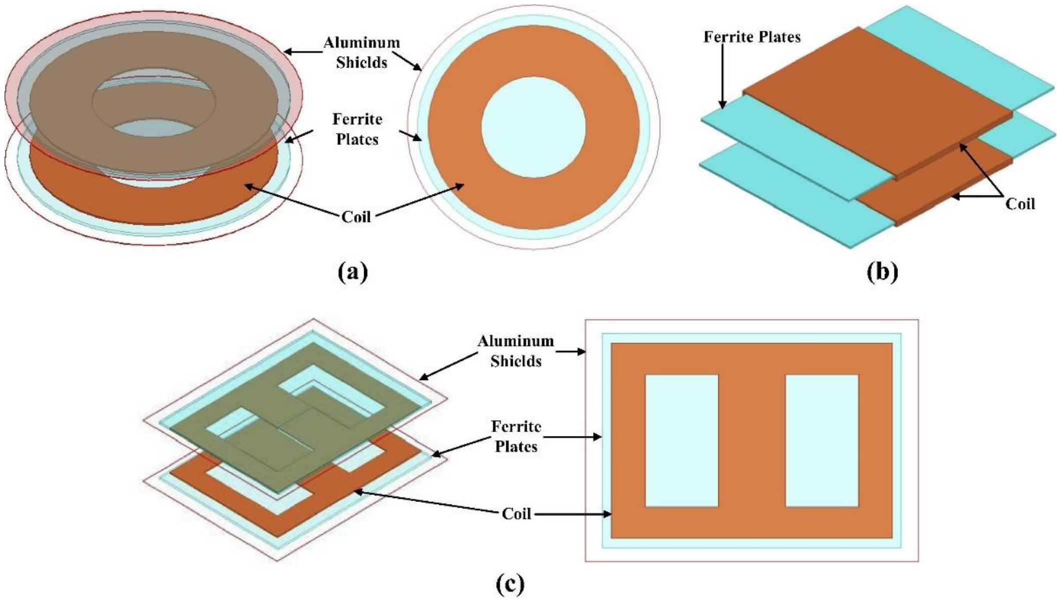


Figure 2.2 Coil systems: (a) circular structure, (b) solenoid structure, and (c) bipolar structure

A more advanced coil design can be found in [26]. Figure 2.3 shows the proposed coil structure, where intermediate L_{int} is embedded into the primary coil structure L_1. L_{int} and its resonant capacitor form a passive resonant circuit, which is energized through coupling effect between L_{int} and L_1. Since there is also a coupling effect between L_{int} and the secondary coil structure L_2, the coupling of the whole coil system is improved. This design claims a higher efficiency than that of a circular coil system, though in terms of tuning it is more complicated.

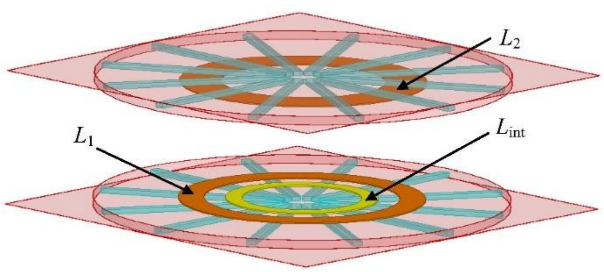


Figure 2.3 Advanced coil structure. L_{int} = intermediate structure; L_1 = primary coil structure; L_2 = secondary coil structure [26]

2.2.2 Coil design for dynamic charging systems

Dynamic charging systems can help further reduce the size of the battery pack on a vehicle and offer the vehicle more convenience and flexibility. There are two kinds of coil structures used in dynamic charging systems for EVs. The major difference between the two coil structures is on the primary coil side: one uses the single-coil design (a long track loop that can still be considered as a coil because of its working principle) [27-29] shown in Figure 2.4(a) and the other employs the segmented-coil design [6, 9, 30, 31] shown in Figure 2.4 (b).

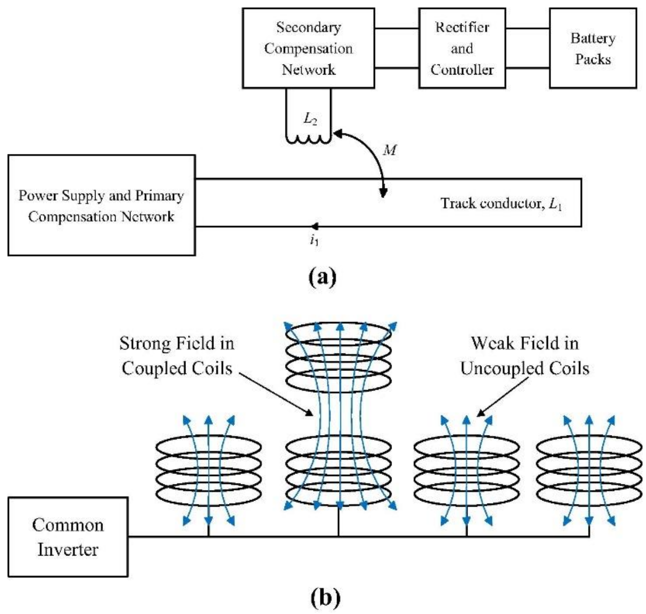


Figure 2.4 Typical coil configurations for dynamic charging systems with (a) single-coil design for primary coil and (b) segmented-coil design for primary coil. L_1 = track conductor; L_2 = receiver coils; M = mutual inductance between L_1 and L_2; i_1 = the (excitation) current in the primary coil [27, 30]

In a single-coil design for the primary coil, the drawback is that when the track conductor (L_1) is not covered by the receiver coils (L_2), it not only generates a redundant EMF, but also results in low efficiency of the whole system. To overcome this problem, researchers from Korea Advanced Institute of Science and Technology (KAIST) proposed a new cross-segmented power supply rail, in which two pairs of power cables were wound in I-type ferrites. By controlling the current direction in the power cables, they were able to power the rails on and off selectively. In addition, the power cables were wound in twisted pairs, which greatly reduced EMF issues [28]. In order to further improve system performance, they introduced a new track rail wound in ultra-slim S-type ferrite cores. The minimal amount of power cables and ferrite cores were employed, reducing the total construction cost. This design had better misalignment tolerance and lower EMF than the rail wound in the I-type cores [29]. Researchers from North Carolina State University (NCSU) used a segmented-coil design for the primary coil and employed the reflected reactance from the secondary coil to self-increase the magnetic field strength in the coupled section between the transmitter and the receiver [30]. As shown in Figure 2.4(b), the magnetic field is strong in the coupled coils and weak in the uncoupled coils. This not only simplifies the control method, but also improves the system efficiency. However, speed-dependent pulsating power is common in this coil design, resulting from the moving vehicle passing over a sequence of coils that causes the alignment and straddling of magnetic fields. The power pulsation can shorten the battery service life and is detrimental to the power grid. Researchers from Oak Ridge National Laboratory (ORNL) had an innovative solution that utilized electrochemical capacitors to smooth power pulsation on both the grid side and vehicle side. They demonstrated that the active parallel combination of lithium-capacitor (LiC) energy storage and the grid supply resulted in very uniform power draw from the grid, where active parallel means that a high-power, bidirectional controllable power flow, DC-DC converter interfaces the LiCs to the DC input of the high-frequency inverter. Furthermore, they installed passive parallel LiCs in vehicle and successfully smoothed the battery currents [31].

2.3 System performance and technical challenges

Table 2.1 summarizes the system parameters of selected stationary charging systems. The efficiency is high at the desirable output power levels, but note that the efficiency measurement is inconsistent in the literature. For example, some studies use AC grid to battery pack measurements, some use DC input to battery pack efficiency, and some report coil efficiency. From the system analysis and sustainability assessment perspectives, it is preferable to know the AC grid to battery pack efficiency as it provides comprehensive characterization of the charger performance and it is directly related to the overall energy consumption assessment and electricity cost calculation for the economic evaluation. It is recommended to consistently report AC grid to battery pack efficiency as a preferred common practice for efficiency measurement.

Table 2.1 Summary of system parameters of selected stationary charging systems

Institute	Power (kW)	Efficiency	Switching frequency (Hz)	Air gap (mm)	Transmitter size (cm^2)	Receiver size (cm^2)	Year	References
Univ. of Auckland	2		20k	200	3848	3848	2011	[20]
	2–7		20k	100-250	3100	3100	2013	[25]
	1	91.3%[c]	85k	100	1385	1385	2015	[26]
UM-Dearborn	3.3	95%[b]	1M	150	1024	1024	2015	[32]
	6	95.3%[b]	95k	150	3600	3600	2015	[33]
	7.7	96%[b]	79k	200	4800	4800	2014	[5]
KAIST	43235		20k	150	9900	1400	2014	[34]
Utah State Univ.	5	90%[a]	20k	175-265	5191	5191	2012	[21]
Saitama Univ.	3	90%[b]	50k	200	960	960	2012	[23]
ETH Zurich	5	96.5%[b]	100k	52	346	346	2015	[35]

[a] AC grid to battery pack efficiency.
[b] DC input to battery pack efficiency.
[c] Coil efficiency.

The sizes of both primary coils and secondary coils are larger than conductive chargers in most cases. Researchers from ETH Zurich developed a relatively compact wireless charging system and the power density is higher than any other system listed in Table 2.1. However, the system may be more sensitive to misalignment than other listed systems. There is a trade-off between compact and lightweight structure and good system performance [36], and balancing the size of the stationary charging system and its misalignment tolerance is an ongoing practical challenge for researchers.

The recent system performance of dynamic charging systems is given in Table 2.2. One challenge in dynamic charging systems is how to improve the system efficiency. The system efficiency is lower for dynamic systems than for stationary charging systems, and this is mainly because a certain amount of magnetic flux generated by the primary coil is not coupled with the secondary coil. The other challenge is how to maximize the amount of energy received by the secondary coils. When the vehicle is at high speed and the track length is limited, it is hard for EVs to get enough energy.

Table 2.2 Summary of system parameters of selected dynamic charging systems

Institute	Power (kW)	Efficiency	Switching frequency (Hz)	Air gap (mm)	Transmitter width (cm)	Receiver size (cm^2)	Year	References
KAIST	3–25	72–83%[a]	20k	10–200	10–140	990–13,600	2009	[7]
ORNL	1.5	75%[b]	23k	100	33	855	2013	[6]
NCSU	0.3	77.82%[b]	100k	170	35	1225	2014	[30]

[a] AC grid to battery pack efficiency.

[b] DC input to battery pack efficiency. KAIST = Korea Advanced Institute of Science and Technology; ORNL = Oak Ridge National Laboratory; NCSU = North Carolina State University.

The system performance of stationary and dynamic wireless chargers is fundamentally determined by the materials. Currently, copper is widely used as the coil material because of its good conductivity and relatively low price. Thin copper strands are twisted and woven together to make litz wires that are employed for winding coils, which not only minimizes the skin effects, but also gives enough current density. Mn-Zn ferrites are selected as the core materials to provide sufficient magnetic shielding at the desired frequencies. Aluminum is used for magnetic shielding because of its competitive performance and cost. With the advent of the new materials, such as high-temperature superconducting (HTS) materials and metamaterials, higher transfer efficiency and longer transmission distance can be achieved. [37] proposed a wireless charging system with copper transmitter coils and HTS receiver coils. Their experimental results showed that both the transfer efficiency and impedance matching were enhanced. Similarly, [38] built a wireless charging system with HTS transmitter coils and copper receiver coils. They proved that with the application of HTS materials, both the transfer efficiency and distance increased. Researchers from Mitsubishi Electric Research Laboratories analyzed the metamaterials, which had negative permeability. They demonstrated that the coupling effect between the two coils was able to be improved and the transfer efficiency was also further boosted with the use of a metamaterial slab [39]. Though their WPT system is not for EV applications, they provide potential possibilities for an EV wireless charging system to transfer power with higher efficiency and longer distance.

2.4 Real-world applications and selected case studies

2.4.1 Public transit buses

Because of the fixed-route attributes of urban transit bus systems, a significant portion of recent development and application of wireless charging has been focused on electric transit buses. A growing number of demonstrations of wireless charging electric bus systems have been reported, as highlighted in Table 2.3.

Table 2.3 Summary of selected wireless charging electric bus projects

Project	Start year	Location	Efficiency	Frequency (Hz)	Power (kW)	Battery capacity (kW h)	Air gap (mm)	References
Bus projects in Italy	2003	Turin, Italy	90%[b]	15–20k	60		40	[40, 41]
KAIST On-Line Electric Vehicle (OLEV)	2009	South Korea	72–83% [a]	20k	6–100		170–200	[7, 42]
Bombardier PRIMOVE IPT for Electric Buses	2010	Germany, Belgium	>90% [b]	20k	40–200	36–90		[7, 43]
Chattanooga Area Regional Transportation Authority (CARTA)	2011	United States (TN)	90% [a]	15–20k	60		40	[40, 44, 45]
Wireless Advanced Vehicle Electrification (WAVE)	2012	United States (UT, CA, TX, MD)	90% [b]	20k	25–50		150–250	[40, 46]
ZTE Corporation projects	2014	China (various cities)	90% [a]	45k	30, 60		200	[47-49]

[a] AC grid to vehicle terminal efficiency.
[b] Measurement terminals unknown.

Wireless charging can eliminate a major stumbling block for deploying urban electric transit buses – the range limitation. According to the Chattanooga Area Regional Transportation Authority (CARTA) project, a short “opportunity charge” of 1 min at 60 kW can extend the range by approximately 1 mile (≈ 1.61 km) so that multiple charges in a day would release the range constraint to cover the required daily route of 100 miles (≈ 161 km), which otherwise requires battery swapping during the day [45].

Another obstacle for the expansion of traditional pure electric transit buses lies in the battery size, cost, and life. For a long-range all-electric bus, the battery pack can comprise about 26% of the weight and 39% of the total cost of the bus [10, 12, 50]. Among the various bus projects, the KAIST On-Line Electric Vehicle (OLEV) project in Korea has advanced technologies that allow buses to charge either while stationary or in motion to significantly downsize the battery. Beginning in 2009, the OLEV research group developed and applied the Shaped Magnetic Field in Resonance (SMFIR) technology in buses and a tram to demonstrate the dynamic wireless charging of EVs as a commercially viable approach [42]. The battery installed on a Gumi City bus is less than one-fifth the size of a normal conductively charged electric bus battery, which significantly reduces the procurement cost of OLEVs [11]. As a result of dynamic wireless charging, the state of charge (SOC) of an OLEV battery can be kept in a narrow 40–60% SOC band that may help extend the battery life, instead of the large 20–90% SOC swing of a normal conductively charged electric bus [51].

2.4.2 Passenger cars

As early as 2012, the U.S. Department of Transportation recognized the emergence of WPT for EV applications and identified the need to understand the implications of dynamic wireless charging of EVs on U.S. highways [13]. In 2015, Utah State University built an advanced test facility for dynamic wireless charging [52]. Dynamic WPT may enable unlimited range extension for EVs [13]. EVs can run continuously without stopping in areas with available dynamic WPT infrastructure. Also, the battery capacity could be reduced to below 20% of a conventional EV battery [53].

Several feasibility studies were conducted to test the idea of deploying a dedicated WPT lane on major roadways for in-motion charging. ORNL partnered with three other U.S. Department of Energy laboratories and conducted a feasibility analysis of dynamic wireless charging using traffic data from Atlanta, GA [54]. The power requirement versus the vehicle speed profile was characterized using data from Argonne National Laboratory's chassis dynamometer testing facility and field tests of advanced vehicles at Idaho National Laboratory. A vehicle speed of 40 miles per hour (≈ 64.37 km/h) was selected to meet the minimal speed requirements for operational status of typical commuter roadways, which corresponds to a power transfer level of 25 kW. This power level is required to sustain vehicle travel and maintain the SOC. A higher power transfer level and relatively higher power from the vehicle propulsion system is required for greater speeds. The arterial routes that maximize roadway electrification return on investment were identified by using information from the National Renewables Energy Laboratory, including the most frequently traveled roadways based on vehicle miles traveled (VMT) and representative traffic volumes versus time of day. The 1% of arterial roads in Atlanta where 17% of VMT took place were selected as the most desirable road segments for charging. The infrastructure proposed to support this system included 12 transformers and inverters per mile (1 mile ≈ 1.61 km) with a 100-m maximum distance between inverter and coil [54]. In addition to research, ORNL is facilitating technology development and standards establishment by partnering with Evatran and Clemson University's International Center for Automotive Research (ICAR) to demonstrate ORNL WPT systems in fully operational original equipment manufacturer (OEM) vehicles in various applications in the spring of 2015 [54]. In Europe, another feasibility study being conducted with test sites in France, Italy, and Sweden is the feasibility analysis and development of on-road charging solutions for future electric vehicles (also called FABRIC). The project duration is from January 2014 to December 2017 with a total cost of 9 million Euros and it seeks to pave the way for large scale deployment of electromobility. It is supported and co-funded by the European Union in the Seventh Framework Programme for Research, Technological Development and Demonstration, European Council for Automotive R&D (EUCAR) and ERTICO-ITS Europe [55].

2.4.3 Other applications

Wireless charging can also be applicable for other transportation modes that require continuous fixed-route operations, such as harbor, airport, rail systems, and theme parks. Transporting commodities from shipping ports to nearby distribution zones is often referred to as drayage operations. "Zero emission" drayage operations are the long term goal of many large port cities and wireless charging can help these vehicles operate continuously and enhance regional sustainable mobility in densely populated areas. The Port of Long Beach in Los Angeles, CA is identified as a candidate for such an implementation to combat the pollution and energy consumption related to the intense drayage operations [54].

2.5 Sustainability, safety and social implications of WPT technology

2.5.1 Energy and environmental assessments

Recent energy and environmental assessments have focused on the comparative analysis of wireless charging electric automobiles versus either conventional powertrain or plug-in charging electric automobiles.

Wireless charging electric buses were found to have better performance than diesel buses in terms of carbon emissions. The CARTA project compared the use phase performance of a wireless charging electric bus to a diesel bus providing the same service. They reported an electric bus reduces CO_2 emissions by approximately 38% (equivalent to a reduction of 567 g per mile), assuming fuel economies of 7 miles per gallon (mpg) for a diesel bus and 1.5 kW h per mile for an electric bus and emission factors of 10,274 g of CO_2 per gallon of diesel and 600 g of CO_2 per kW h of U.S. average electricity (1 mile ≈ 1.61 km; 1 gallon ≈ 3.785 l) [45]. However, these results are use-phase only and lack the comprehensive perspective that a life cycle assessment also encompassing the burden of manufacturing, infrastructure deployment, and end-of-life would provide.

Wireless charging electric buses were found to have comparable performance with plug-in charging electric buses in terms of energy and greenhouse gas (GHG) emissions from a life cycle scope. The positive implication of wireless charging in terms of energy and environmental performance lies in the requirement of a downsized battery that significantly reduces vehicle weight and helps improve the fuel economy. The trade-off is the requirement of large-scale charging infrastructure deployment. In order to understand the energy and environmental trade-offs of wireless charging technology, a life cycle analysis has been conducted as part of this dissertation to compare plug-in versus stationary wireless charging technologies and illustrated the trade-off of the infrastructure burdens versus the battery-related savings by modeling an existing bus system in Ann Arbor, MI over a 12-year time frame [10]. Two main conclusions were drawn from this study: (1) although there are additional energy and GHG emission burdens from the wireless charging infrastructure for transit buses, the benefits of battery downsizing can offset these burdens so that a wireless charging all-electric bus system would still be attractive in energy and environmental terms; (2) the bottleneck for further enhancing the sustainability of wireless charging mainly lies in the grid-to-battery charging efficiency. The wirelessly charged battery was shown to be 27–44% the size of a plug-in charged battery. Although the associated reduction of 12–16% in bus weight for the wireless buses can induce a reduction of 5.4–7.0% in battery-to-wheel energy consumption, the relatively lower wireless charging efficiency could cancel out this lightweighting benefit from a primary energy perspective. As a result, a similar cumulative energy demand and global warming impact were obtained in the use phase for both charging technologies [10]. With the current technical maturity, the energy and environmental impact of wireless charging technology is similar to the plug-in charging technology from a life cycle perspective. However, further advances in charging efficiency and renewable energy penetration into the daytime or peak-hour electricity grid (provided that majority of wireless charging is during the daytime and the majority of plug-in charging is overnight) would enhance the sustainability performance of a wireless charging bus system [10].

Researchers at Utah State University [56] developed a model to evaluate the environmental impacts and techno-economic feasibility of dynamic WPT applied to interstate and urban roadways in the U.S., compared to conventional internal combustion engine vehicles (ICEVs). They reported that a light duty WPT EV has a 49% CO_2 reduction compared to a light duty ICEV as well as some reduction in the criteria pollutants, such as VOC, CO, NO_x, PM10, and PM2.5, except SO_x [56]. An increase in SO_x is primarily due to the dominance of coal, which was assumed to represent 39% of the U.S. power grid for the WPT EVs [56]. For both light duty vehicles and trucks in the U.S., a reduction of 10.1% in total CO_2 emissions was reported assuming a 20% market penetration [56]. They also reported 2.6 years of societal payback time for the infrastructure at a 20% market penetration, resulting from the cost savings associated with the operation, maintenance, and purchase of the WPT vehicle architecture and roadway [56]. Although dynamic wireless charging electric automobiles showed good environmental performance compared to conventional powertrain vehicles, its environmental performance relative to the plug-in charging alternative is yet to be examined in the literature.

For the energy and environmental assessment of highway dynamic wireless charging for passenger cars, the design of coil pitch that characterizes the longitudinal space between the adjacent coils is the key to analyzing the trade-off of infrastructure burden versus use phase performance. A coil pitch of 70% was used in the ORNL two-coil apparatus, resulting in a longitudinal gap between the adjacent coils. The power transfer minimum is 50% of full power when the receiver coil is midway between the transmitter coils [13]. Lower-density and separated power transfer pads would reduce material consumption and thus lower the infrastructure burdens, but it could result in a decrease of energy transmitted to the moving vehicle and pose large fluctuations on the grid attributable to the varying charging power demand [55]. Thus, an optimal coil pitch design is needed to minimize infrastructure burdens while still maintaining an acceptable level of power transfer.

Prospective energy and environmental assessments would need to incorporate the spatial and temporal heterogeneity of additional demand on the electricity grid from wireless charging

EVs. For example, the power demand from in-motion WPT EV systems would be dynamic across both time and space [13]. There is an anticipated extra burden of energy supply on electricity load profiles as the demand from the dynamic WPT EVs is likely during peak hours of electricity consumption [13]. It would be useful for future work to compare the environmental assessment results between marginal and average grid emission intensities [57] to better understand the consequential/marginal environmental impacts of WPT EV adoption. Researchers have also proposed an optimization framework linking traffic assignment with power distribution in order to have a better understanding about transportation electrification and to answer these questions: (1) How many drivers are going to use the charging-in-motion services, in which locations, and at what time frame? (2) What level of power demand is expected in these locations, and what is the optimal operational plan for electric power distribution to respond to the demand? [58] Vehicle-to-grid (V2G) and grid-to-vehicle (G2V) communication and management should be another key aspect of prospective energy and environmental assessment of wireless charging technology. Instead of posing additional demand at peak load times, EVs have the potential for electricity load shifting, and their batteries provide storage for variable and transient energy sources, such as wind and solar power, that produce electricity in excess of current demand [53, 59]. In the future, EV recharging would be expected to interact with a smart grid in sophisticated and optimal management strategies, and more energy and environmental analyses would be required to investigate these impacts.

The continuous V2G and G2V communication and constant dynamic wireless charging on arterial roads would lead to a full vehicle autonomy and unconstrained range extension, at least where WPT infrastructure is deployed. Future environmental and energy assessment should address the rebound effect brought by this emerging technology due to the convenience of wireless charging technology and reduced range anxiety [60], that is, the growth of environmental impacts due to the increase in VMT could offset the relative reduction of environmental impacts due to battery downsizing, vehicle lightweighting, and fuel economy improvement.

2.5.2 Economic and policy analyses

The economic competitiveness of wireless charging technology is influenced by three main components of the product life cycle: charging infrastructure; battery; and use phase energy costs.

Compared to the wired charging hardware, the major difference with a wireless charger for a stationary WPT design is the two magnetic couplers which bring an extra material cost of about US$400 for an 8 kW charger [53]. The cost increase for WPT charging hardware can be quite acceptable considering the convenience, battery downsizing, and long-term operation cost savings brought by wireless charging [40]. Wireless bus charging can reduce fuel costs by over 80% (US$90,000) over the vehicle's life compared to a diesel bus [45]. For dynamic wireless charging on highways, it is noteworthy that the infrastructure investment would be cost effective given that the U.S. interstate highways make up only about 1% of roadway miles, yet they carry 22% of all miles traveled [61]. Meanwhile the utilization of the installed infrastructure can be high due to a large number of vehicles traveling on the same roadway segments [9]. Given more opportunity for charging while driving, dynamic wireless charging can further mitigate the high purchase cost of EVs by allowing a substantially downsized onboard energy-storage system [9], which lightweights the vehicle and would further improve the overall energy and economic performance during operation [10, 62]. Wireless charging electric buses were found to be more economically competitive than conventional diesel, diesel hybrid and plug-in charging electric buses in a life cycle scope [62], but the life cycle economic performance of dynamic wireless charging cars is not well established yet. Current available cost data for wireless charging obtained from the literature, government reports, and manufacturers are summarized in Table 2.4.

Table 2.4 Reported economic data for wireless charging systems

Model or real case	**Cost scope**	**Mode**	**Vehicle**	**Location**	**Cost**	**Note**	**Source**
Model	Life cycle	Stationary	Bus	Ann Arbor, MI	$0.99/bus-km	Infrastructure + use phase, also includes bus cost	[62]
Model	Infrastructure only	Dynamic	Car	Atlanta, GA	$2.8 million/lane-mile	Hardware + deployment including labor	[54]
Model	Infrastructure only	Dynamic	Car	Atlanta, GA	$350,000/lane-mile	Grid connection cost only	[54]
Model	Infrastructure only	Dynamic	Car + Truck	United States	$2.4 million/lane-mile	WPT electronics + electric power delivery infrastructure	[56]
Real case	Infrastructure only	Dynamic	Bus	Korea	$0.85–1.07 million/km	Electronic components and construction for two-way roads	[7]
Real case	Infrastructure only	Dynamic	Bus	Korea	$15,000 (fixed) + $200/m (variable) per station	Fixed cost mainly includes the inverter cost and the labor cost to connect it to the grid. The variable cost depends on the length of the power transmitter	[63]
Real case	Charger only	Stationary	Car	Worldwide	$1940–$2440 per 3.3 kW charger	Wireless chargers sold by Plugless Power	[64]
Real case	Use phase only	Stationary	Bus	Italy	$9000/bus-year	Electricity cost	[40]
Real case	Use phase only	Stationary	Bus	Chattanooga, TN	<$0.10/bus-mile	Energy cost	[45]

Note: All currency is U.S. dollars; 1 mile $\approx$ 1.60934 km.

A key issue in the economic analysis of wireless charging technology lies in the economic allocation of charging infrastructure and determination of battery capacity. More wireless charging stations deployed will lead to a requirement of a smaller onboard battery, and vice versa. Trade-off of these two design variables has been evaluated in several optimization studies to minimize the investment cost of a wireless charging bus route in Korea [63, 65, 66]. The cost function to be minimized consists of the battery cost and cost of the power transmitters. The power transmitter cost is made up of a fixed cost and a variable cost. Fixed cost mainly includes the inverter cost (one for each power transmitter) and the labor cost to connect it to the grid. The variable cost depends on the length of the power transmitter [63]. Further studies are needed to extend this optimization framework to a network of multiple bus routes with interconnected charging stations where the utilization of each charging station can be increased. The cost function would also need to be extended to include not only the capital cost but also the use phase cost (battery replacement, charger maintenance, and electricity costs). For highway dynamic wireless charging for passenger cars, a framework to optimize the distribution of charging infrastructure and battery capacity with the minimum life cycle cost is yet to be established.

Road infrastructure improvements and increasing EV sales need to be coordinated by a portfolio of policy instruments to guide the proper deployment of wireless charging infrastructure. This massive transformation in personal and commercial electric mobility would require a focused long-term strategy and large scale infrastructure planning and deployment for targeted municipalities [54]. If WPT for EVs is demonstrated to enhance sustainable mobility, it would require government subsidies and incentives to enable penetration of this new and disruptive technology and guide the synergistic deployment of WPT technologies and the increasing penetration of EVs in the auto market [54]. In order to characterize the impact of advanced technologies on consumer behavior, ORNL developed the Market Acceptance of Advanced Automotive Technologies (MA3T) model and predicted that dynamic wireless charging could boost the EV share of light duty vehicle (LDV) sales to more than 60% by 2050. In comparison, when there is no dynamic WPT system deployment throughout the timeline, the share can only reach 20–30% by 2050 [54, 67]. EV sales boosted by WPT technology would be of value for car manufacturers as it will be a technology multiplier to credit their fleet corporate average fuel economy (CAFE) figures in the 2025 calculations [54]. To guide policy makers on infrastructure deployment, researchers tested three vehicles (a compact car: Honda Insight, a large car: Chevrolet Impala, and an SUV: Ford Explorer) to find out the infrastructure coverage required for 300 mile (≈ 482.8 km) range (30 kW delivered to the vehicle). They found that a coverage of 0.46–1% of lane-miles is required for the UDDS city drive cycle, a 17–43.8% coverage is required for the HWFET highway drive cycle, and a 17.2–64.3% coverage is required for the HW-MTN (highway driving in a mountainous region) drive cycle [9, 68]. They concluded that if only 1% of the roadway is powered in urban areas, most vehicle types can easily reach the 300-mile target range with a relatively small battery pack [9, 68].

2.5.3 Health and safety

Although the road-embedded WPT technologies would improve system operational safety (since there are no exposed high voltage cables or power outlets as plug-in vehicles) [40], significant research has been conducted [6, 21, 69, 70] to investigate the EMF issues with human electromagnetic exposure limits. Well-defined biological responses caused by exposure to electric and magnetic fields below 100 kHz include annoyance, surface electric-charge effects, the stimulation of central and peripheral nervous tissues, and the induction in the retina of phosphenes (a perception of faint flickering light in the periphery of the visual field) [71]. The EMF may also induce high field strengths and heating in nearby human bodies, implanted medical devices, small animals, and metals. The two most prevailing exposure limits are those published by the Institute for Electrical and Electronic Engineers (IEEE) and the International Commission on Non-Ionizing Radiation Protection (ICNIRP) [44]. For example, ICNIRP [71] sets limitations on both electric fields and magnetic fields. For electric fields, a human body is a good conductor. The external electric field will induce an electric field inside the human body. ICNIRP has a limit on the internal electric fields of all human tissues, which cannot exceed 1.35×10^{-4} times the frequency value. Furthermore, ICNIRP has a limit on general public exposure to electric fields, which is set to be 83 V/m. For magnetic fields, the tissue has the same permeability as air. The tissue has the same magnetic flux density with that of the external field. ICNIRP has a limit on general public exposure to magnetic fields, which is updated as 27 μT in 2010. Additionally, 6.25 μT, which was the limit set in 1998, is still commonly used in recent experiments.

Current research found that EMF can be effectively controlled within acceptable levels, but further research is still required to ensure health and safety under variable conditions and as the technology evolves. For transit buses, researchers characterized potential exposure of people to the fields associated with a wireless charging electric bus operated by CARTA in Tennessee. They found that during charging none of the magnetic or electric fields measured either inside or outside the bus exceeded the IEEE or the ICNIRP limits for the general public [44]. Researchers can effectively shield the EMF from affecting passengers onboard by utilizing aluminum plates at the back of the secondary pad to protect the interior of the vehicle and aluminum rings at both the primary and secondary pads to limit the stray field in the lateral direction [9, 40]. The eddy currents generated when the magnetic flux passes through the aluminum shield will induce a new magnetic flux that is in the opposite direction of the original magnetic flux, resulting in an effect of shielding the original magnetic flux. For dynamic wireless charging of in-motion passenger cars, researchers at ORNL [6] controlled the EMF at 23 kHz within the acceptable standards for the general public of 6.25 μT set by the ICNIRP by utilizing aluminum shielding. Further research, however, is still required to ensure health and safety of dynamic charging under open traffic environments that have more unforeseeable conditions than for lab test environments, such as variable power levels required for light-duty and heavy-duty vehicles under varying speeds and accidental leakage exposure to nearby passing pedestrians, cyclers, and patients with implanted medical devices. Living object detection systems and foreign object detection systems are required for detecting subjects and metals nearby.

2.5.4 Prospects to enhance sustainable mobility

Challenges and opportunities coexist in the near-term and long-term development of WPT technology for sustainable transportation. A series of technical and sustainability challenges and opportunities are identified in Table 2.5.

Table 2.5 Prospects to enhance sustainable mobility – coexistence of challenges and opportunities of WPT technology

	Short description	Detailed description
Challenges [13, 31, 55]	Maintenance of dynamic alignment	Lateral alignment for lane keeping and optimal power transfer coupling for dynamic charging
	Charger life and durability	Need to remain in the road without degrading the structure for at least 20 years and cope with resurfacing works every 10–12 years
	Utility power distribution	Connect and distribute the power supply to the point of charging event
	Burden on electricity grid	Multiple vehicles on charging lane and power flow management
	Synchronization of energizing coils	Low-latency private and secure vehicle-to-infrastructure communications for roadway coil excitation sequencing
	Economic management	Time of use and revenue structure
	Health and safety	Leakage fields: the magnetic and electric fringe fields associated with high frequency magnetic resonance power transfer
	Tolerance for diverse power demands	Acceptable power levels versus different vehicle class types (car, truck, bus, etc.)
Opportunities	New materials	With the advent of the new materials, such as high-temperature superconducting (HTS) materials and metamaterials, higher transfer efficiency can be achieved [37-39]
	Dynamic charging: range extension	Depending on the power capability, the use of dynamic charging would further increase driving range and reduce the size of the battery pack [9]
	Coupling with automated vehicles (AVs)	AVs would accelerate the adoption for WPT technology by leveraging capabilities such as charging alignment precision by lane-following technologies to keep proper alignment between the vehicle and the grid power supply units and improve the driving performance and energy efficiency [54]
	Vehicle connectivity	Vehicle connectivity and communication will be required for proper system effectiveness: both with the grid and other vehicles as well as vehicle speed control [54]
	Automated highway system (AHS)	This concept called for continued personal ownership of the vehicle, but capable of commuting on traditional highways and streets in addition to a higher speed operation on an automated guideway. The highway carrying capacity could be dramatically increased to more than 2500 vehicle/hour/lane and remain environmentally sustainable [13]

2.6 Conclusions

This chapter contains a review of the status of WPT development and applications in the transportation sector. The challenges and opportunities in terms of technology and sustainability performance have been enumerated and discussed.

The first section was a review of the technical aspects of both stationary and dynamic charging systems in three areas: (1) coil design; (2) compensation topologies; and (3) power electronics converters and control methods. Progress in technology has led to improved system performance. Stationary wireless charging systems have comparable system performance to conductive charging systems, and dynamic wireless charging systems are on the path to achieve the charging of vehicles in motion. From the technical perspective, major research gaps are: (1) how to improve the system efficiency of dynamic charging systems and maximize the amount of energy received by vehicles at high speed in a limited charging lane range; and (2) how to balance the size of the charging system and its misalignment tolerance and efficiency.

From the sustainability perspective, WPT EVs have the trade-off of large infrastructure deployment versus the benefits of battery downsizing and vehicle lightweighting. WPT technology offers the possibilities for better energy performance, lower environmental impacts, lower life cycle cost, and more convenience and operational safety benefits compared to wired EVs and conventional ICEVs. In order to realize these possibilities of WPT EVs, the following research gaps need to be filled: (1) electricity grid management that balances the demand and supply of electricity for both static and moving vehicles; (2) optimization of large scale charging infrastructure deployment and battery capacity with a consideration of battery life for both public transit and passenger car applications; and (3) policies that coordinate the growth and development of WPT technology with other emerging EV technologies, such as connected and automated vehicles (CAVs).

Challenges and opportunities remain in the design and deployment of WPT EV systems. Dynamic wireless charging offers opportunities for sustaining the battery charge while driving so that the large battery pack that represents a bottleneck for deploying EVs can be eliminated and range anxiety will be reduced. The environmental, economic and societal impacts of large scale infrastructure deployment and performance in terms of energy efficiency, durability, and reliability must be carefully evaluated for prospective real-world deployment of dynamic WPT EVs. Stationary WPT for residential and commercial charging is expected to have earlier widespread adoption than dynamic charging given its technical maturity and economic feasibility, while dynamic WPT could be implemented gradually if the market develops enough to significantly lower the high initial infrastructure cost. Connected and automated vehicles (CAVs) would provide strong synergy and accelerate the adoption of WPT technology by leveraging capabilities (such as charging alignment precision) to improve driving performance and energy efficiency. WPT technology also offers more active connectivity with the electric grid through V2G and G2V bidirectional power transfer, enabling EVs to become mobile energy storage devices to help regulate the grid by storing excess generation from uncontrolled renewables. In the next decade, improvements of WPT in these areas will determine how significant the role of WPT technology will be in advancing vehicle electrification and improving the sustainability of electrified mobility.

References

[1] Tesla N. Art of transmitting electrical energy through the natural mediums. U.S. Patent 787412; April 18, 1905.

[2] Tesla N. Apparatus for transmitting electrical energy. U.S. Patent 1119732; December 1, 1914.

[3] Zhang Y, Zhao Z, Chen K. Frequency-splitting analysis of four-coil resonant wireless power transfer. IEEE Trans Ind Appl 2014;50(4):2436-45.

[4] Zhang W, White JC, Abraham AM, Mi CC. Loosely coupled transformer structure and interoperability study for EV wireless charging systems. IEEE Trans Power Electron 2015;30(11):6356-67.

[5] Nguyen TD, Li S, Li W, Mi CC. Feasibility study on bipolar pads for efficient wireless power chargers. In: 2014 twenty-ninth annual IEEE applied power electronics conference and exposition (APEC), 16-20 March. IEEE; 2014. p. 1676-82.

[6] Onar OC, Miller JM, Campbell SL, Coomer C, White CP, Seiber LE. A novel wireless power transfer for in-motion EV/PHEV charging. In: 2013 twenty-eighth annual IEEE applied power electronics conference and exposition (APEC). IEEE; 2013. p. 3073-80.

[7] Choi SY, Gu BW, Jeong SY, Rim CT. Advances in wireless power transfer systems for roadway-powered electric vehicles. IEEE J Emerg Sel Topics Power Electron 2015;3(1):18-36.

[8] Kurs A, Karalis A, Moffatt R, Joannopoulos JD, Fisher P, Soljačić M. Wireless power transfer via strongly coupled magnetic resonances. Science 2007;317(5834):83-6.

[9] Lukic S, Pantic Z. Cutting the cord: Static and dynamic inductive wireless charging of electric vehicles. IEEE Electrification Magazine: IEEE; 2013. p. 57-64.

[10] Bi Z, Song L, De Kleine R, Mi C, Keoleian GA. Plug-in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. Appl Energ 2015;146:11–9.

[11] Thornton J. Pulling power from the road: Charged by the route it follows, an electric bus gets a real world test. Mechanical Engineering: ASME; 2014. p. 44-9.

[12] Reikes J at BYD Motors Inc., Personal communication; July 21, 2014.

[13] Miller JM, Jones PT, Li J-M, Onar OC. ORNL experience and challenges facing dynamic wireless power charging of EV's. IEEE Circ Syst Mag: IEEE; 2015. p. 40-53.

[14] Musavi F, Eberle W, Dunford WG. A high-performance single-phase bridgeless interleaved PFC converter for plug-in hybrid electric vehicle battery chargers. IEEE Trans Ind Appl 2011;47(4):1833-43.

[15] Zhu Q, Wang L, Liao C. Compensate capacitor optimization for kilowatt-level magnetically resonant wireless charging system. IEEE Trans Ind Electron 2014;61(12):6758-68.

[16] Zhu Q, Guo Y, Wang L, Liao C, Li F. Improving the misalignment tolerance of wireless charging system by optimizing the compensate capacitor. IEEE Trans Ind Electron 2015;62(8):4832-6.

[17] Bloom MA, Niu G, Krishnamurthy M. Design considerations for wireless electric vehicle charging. In: 2013 IEEE transportation electrification conference and expo (ITEC). IEEE; 2013. p. 1-6.

[18] Hui SYR, Zhong W, Lee CK. A critical review of recent progress in mid-range wireless power transfer. IEEE Trans Power Electron 2014;29(9):4500-11.

[19] Covic GA, Boys JT. Inductive power transfer. Proc IEEE 2013;101(6):1276-89.

[20] Budhia M, Covic GA, Boys JT. Design and optimization of circular magnetic structures for lumped inductive power transfer systems. IEEE Trans Power Electron 2011;26(11):3096-108.

[21] Wu HH, Gilchrist A, Sealy KD, Bronson D. A high efficiency 5 kW inductive charger for EVs using dual side control. IEEE Trans Ind Informat 2012;8(3):585-95.

[22] Budhia M, Covic G, Boys J. A new IPT magnetic coupler for electric vehicle charging systems. In: IECON 2010 - 36th annual conference on IEEE industrial electronics society. IEEE; 2010. p. 2487-92.

[23] Takanashi H, Sato Y, Kaneko Y, Abe S, Yasuda T. A large air gap 3 kW wireless power transfer system for electric vehicles. In: 2012 IEEE energy conversion congress and exposition (ECCE). IEEE; 2012. p. 269-74.

[24] Park C, Lee S, Cho G-H, Rim CT. Innovative 5-m-off-distance inductive power transfer systems with optimally shaped dipole coils. IEEE Trans Power Electron 2015;30(2):817-27.

[25] Budhia M, Boys JT, Covic GA, Huang CY. Development of a single-sided flux magnetic coupler for electric vehicle IPT charging systems. IEEE Trans Ind Electron 2013;60(1):318-28.

[26] Kamineni A, Covic GA, Boys JT. Analysis of coplanar intermediate coil structures in inductive power transfer systems. IEEE Trans Power Electron 2015;30(11):6141-54.

[27] Kissin MLG, Covic GA, Boys JT. Steady-state flat-pickup loading effects in polyphase inductive power transfer systems. IEEE Trans Ind Electron 2011;58(6):2274-82.

[28] Choi S, Huh J, Lee WY, Lee SW, Rim CT. New cross-segmented power supply rails for roadway-powered electric vehicles. IEEE Trans Power Electron 2013;28(12):5832-41.

[29] Choi SY, Jeong SY, Gu BW, Lim GC, Rim CT. Ultraslim S-type power supply rails for roadway-powered electric vehicles. IEEE Trans Power Electron 2015;30(11):6456-68.

[30] Lee K, Pantic Z, Lukic SM. Reflexive field containment in dynamic inductive power transfer systems. IEEE Trans Power Electron 2014;29(9):4592-602.

[31] Miller JM, Onar OC, White C, Campbell S, Coomer C, Seiber L, et al. Demonstrating dynamic wireless charging of an electric vehicle: The benefit of electrochemical capacitor smoothing. IEEE Power Electronics Magazine: IEEE; 2014. p. 12-24.

[32] Lu F, Zhang H, Hofmann H, Mi C. A high efficiency 3.3 kW loosely-coupled wireless power transfer system without magnetic material. In: 2015 IEEE energy conversion congress and exposition (ECCE). IEEE; 2015. p. 2282-6.

[33] Li W, Zhao H, Li S, Deng J, Kan T, Mi CC. Integrated LCC compensation topology for wireless charger in electric and plug-in electric vehicles. IEEE Trans Ind Electron 2015;62(7):4215-25.

[34] Choi SY, Huh J, Lee WY, Rim CT. Asymmetric coil sets for wireless stationary EV chargers with large lateral tolerance by dominant field analysis. IEEE Trans Power Electron 2014;29(12):6406-20.

[35] Bosshard R, Kolar JW, Mühlethaler J, Stevanovic I, Wunsch B, Canales F. Modeling and η-α-Pareto optimization of inductive power transfer coils for electric vehicles. IEEE J Emerg Sel Topics Power Electron 2015;3(1):50-64.

[36] Covic GA, Boys JT. Modern trends in inductive power transfer for transportation applications. IEEE J Emerg Sel Topics Power Electron 2013;1(1):28-41.

[37] Kim DW, Chung YD, Kang HK, Yoon YS, Ko TK. Characteristics of contactless power transfer for HTS coil based on electromagnetic resonance coupling. IEEE Trans Appl Supercond 2012;22(3):1-4.

[38] Chung YD, Lee CY, Kang HK, Park YG. Design consideration and efficiency comparison of wireless power transfer with HTS and cooled copper antennas for electric vehicle. IEEE Trans Appl Supercond 2015;25(3):1-5.

[39] Wang B, Yerazunis W, Teo KH. Wireless power transfer: Metamaterials and array of coupled resonators. Proc IEEE 2013;101(6):1359-68.

[40] Brecher A, Arthur D. Review and evaluation of wireless power transfer (WPT) for electric transit applications. Washington, DC: U. S. Department of Transportation; 2014.

[41] Conductix-Wampfler. Product overview: Inductive power transfer - IPT. Omaha, NE: Conductix-Wampfler; 2012.

[42] Suh IS, Kim J. Electric vehicle on-road dynamic charging system with wireless power transfer technology. In: 2013 IEEE international electric machines & drives conference (IEMDC), 12-15 May. IEEE; 2013. p. 234-40.

[43] Bombardier PRIMOVE team. Projects of Bombardier PRIMOVE, http://primove.bombardier.com/; 2015 [accessed June 2015].

[44] Tell RA, Kavet R, Bailey JR, Halliwell J. Very-low-frequency and low-frequency electric and magnetic fields associated with electric shuttle bus wireless charging. Radiat Prot Dosim 2014;158(2):123-34.

[45] Bailey JR, Hairr ME. Wayside charging and hydrogen hybrid bus: Extending the range of electric shuttle buses. Washington, DC: U.S. Department of Transportation Federal Transit Administration; 2012.

[46] WAVE team. WAVE Projects, http://www.waveipt.com/; 2015 [accessed June 2015].

[47] ZTE Corporation. Launch of the first pre-commercial bus route in China deploying buses with high-power wireless-charging system, http://wwwen.zte.com.cn/en/about/investor_relations/announcement/201409/P020140918693716018772.pdf; 2014 [accessed November 2015].

[48] ZTE Corporation. ZTE innovative auto wireless charging solution, https://www.itu.int/en/ITU-T/extcoop/cits/Documents/ITS%20Events-201507-Beijing/Presentations/S1P4-Academus-Tian.pdf; 2015 [accessed November 2015].

[49] ZTE Corporation. Leading industrial solution and commercial implementation case study in China, http://www.apec-conf.org/wp-content/uploads/IS-12.4.pdf; 2015 [accessed November 2015].

[50] BYD Auto Company. 2013 BYD 40-ft electric bus specs, http://www.byd.com/la/auto/ebus.html; 2013 [accessed May 2014].

[51] Suh IS, Gu Y. Application of shaped magnetic field in resonance (SMFIR) technology to future urban transportation. In: CIRP design conference 2011. 2011. p. 226-32.

[52] Morris C. The dynamic road ahead: Utah State University builds the nation's most advanced test facility for dynamic wireless charging. Charged EVs: chargedevs.com; Nov/Dec 2014. p. 82-7.

[53] Li S, Mi C. Wireless power transfer for electric vehicle applications. IEEE J Emerg Sel Topics Power Electron 2014;3(1):4-17.

[54] Jones PT, Onar O. Impact of wireless power transfer in transportation: Future transportation enabler, or near term distraction. In: 2014 IEEE international electric vehicle conference (IEVC). IEEE; 2014. p. 1-7.

[55] Naberezhnykh D. Feasibility analysis and development of on-road charging solutions for future electric vehicles: Dynamic Wireless Power Transfer, http://www.fabric-project.eu/images/Presentations/CERV_2015_-_Denis_Naberezhnykh_-_FABRIC_-_V1.pdf; 2015 [accessed June 2015].

[56] Quinn JC, Limb BJ, Pantic Z, Barr P, Zane R. Techno-economic feasibly and environmental impact of wireless power transfer roadway electrification. In: 2015 IEEE wireless power transfer conference (WPTC). IEEE; 2015. p. 1-3.

[57] Zivin JSG, Kotchen MJ, Mansur ET. Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. J Econ Behav Organ 2014;107:248-68.

[58] Li J-M, Jones PT, Onar O, Starke M. Coupling electric vehicles and power grid through charging-in-motion and connected vehicle technology. In: 2014 IEEE international electric vehicle conference (IEVC). IEEE; 2014. p. 1-7.

[59] Huang X, Qiang H, Huang Z, Sun Y, Li J. The interaction research of smart grid and EV based wireless charging. In: 2013 IEEE vehicle power and propulsion conference (VPPC). IEEE; 2013. p. 1-5.

[60] Miller SA, Keoleian GA. Framework for analyzing transformative technologies in life cycle assessment. Environ Sci Technol 2015;49(5):3067-75.

[61] Wu HH, Gilchrist A, Sealy K, Israelsen P, Muhs J. A review on inductive charging for electric vehicles. In: 2011 IEEE international electric machines & drives conference (IEMDC), 15-18 May. IEEE; 2011. p. 143-7.

[62] Bi Z, De Kleine R, Keoleian GA. Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system. J Ind Ecology 2016;21(2):344-55.

[63] Jang YJ, Suh ES, Kim JW. System architecture and mathematical models of electric transit bus system utilizing wireless power transfer technology. IEEE Syst J 2015;PP(99):1-12.

[64] Plugless Power. Plugless Power website, https://www.pluglesspower.com/; 2015 [accessed June 2015].

[65] Jeong S, Jang YJ, Kum D. Economic analysis of the dynamic charging electric vehicle. IEEE Trans Power Electron 2015;30(11):6368-77.

[66] Ko YD, Jang YJ. The optimal system design of the online electric vehicle utilizing wireless power transmission technology. IEEE Trans Intell Transp Syst 2013;14(3):1255-65.

[67] Lin Z, Li J, Dong J. Dynamic wireless power transfer: Potential impact on plug-in electric vehicle adoption. SAE Technical Paper 2014-01-1965; 2014.

[68] Pantic Z, Bai S, Lukic SM. Inductively coupled power transfer for continuously powered electric vehicles. In: IEEE vehicle power and propulsion conference (VPPC). IEEE; 2009. p. 1271-8.

[69] Christ A, Douglas MG, Roman JM, Cooper EB, Sample AP, Waters BH, et al. Evaluation of wireless resonant power transfer systems with human electromagnetic exposure limits. IEEE Trans Electromagn Compat 2013;55(2):265-74.

[70] Ding P-P, Bernard L, Pichon L, Razek A. Evaluation of electromagnetic fields in human body exposed to wireless inductive charging system. IEEE Trans Magn 2014;50(2):1037-40.

[71] International Commission on Non-Ionizing Radiation Protection. Guidelines for limiting exposure to time-varying electric and magnatic fields (1 Hz - 100 kHz). Health Phys 2010;99(6):818-36.

CHAPTER 3

Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system

Abstract

An integrated life cycle assessment and life cycle cost (LCC) model was developed to compare the life cycle performance of plug-in charging versus wireless charging for an electric bus system. The model was based on a bus system simulation using existing transit bus routes in the Ann Arbor-Ypsilanti metro area in Michigan. The objective is to evaluate the LCCs for an all-electric bus system utilizing either plug-in or wireless charging and also compare these costs to both conventional pure diesel and hybrid bus systems. Despite a higher initial infrastructure investment for off-board wireless chargers deployed across the service region, the wireless charging bus system has the lowest LCC of US$0.99 per bus-kilometer among the four systems and has the potential to reduce use-phase carbon emissions attributable to the lightweighting benefits of on-board battery downsizing compared to plug-in charging. Further uncertainty analysis and sensitivity analysis indicate that the unit price of battery pack and day or night electricity price are key parameters in differentiating the LCCs between plug-in and wireless charging. Additionally, scenario analyses on battery recycling, carbon emission pricing, and discount rates were conducted to further analyze and compare their respective life cycle performance.

3.1 Introduction

Conventional powertrain vehicles are mostly propelled by the combustion of fossil fuels that produce emissions of greenhouse gases (GHGs). Electrified vehicles offer an opportunity to mitigate global warming and fossil energy scarcity, and reduce air pollutants in urban environment [1, 2]. Hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) are slowly gaining market share [3]. BEVs, however, require larger batteries than HEVs and PHEVs, and they still face obstacles with commercialization as a result of the heavy and expensive on-board battery packs [4]. Another challenge for electric vehicles lies in the charging method. Conventional plug-in charging can be inconvenient and requires waiting time to recharge the vehicle [4].

The emergence of wireless charging technology for electric vehicles can overcome these two problems of plug-in charging [5-10]. Wireless charging occurs by electromagnetic resonance between two contactless coil plates: one equipped on the bottom of the vehicle (on-board), another paved in the roadway (off-board), as detailed in Chapter 2. Such a configuration allows charging on the roadway without the need to handle the charging cable and coupler, and it is especially applicable to fixed-route vehicles, such as transit buses. Wireless charging is categorized as stationary wireless charging and dynamic wireless charging (charging while vehicles are in motion). In this study, wireless charging refers specifically to stationary wireless charging, which means that wireless chargers are only deployed at some bus stations and a parking lot for buses to charge when they drop off and pick up passengers or park overnight. Because of the frequent charging opportunities available during bus operation, it is feasible to carry a smaller on-board battery and lightweight the vehicle. This mass reduction of the bus can improve fuel economy and has important implications for reducing life cycle energy consumption, GHG emissions, and costs.

Despite the convenience of wireless charging and its potential economic benefits from battery downsizing and vehicle lightweighting, there are significant costs related to initial infrastructure investment, including the procurement and installation of wireless chargers. Compared to the smaller scale of plug-in charging infrastructure, which is usually confined to a parking lot or facility, wireless charging infrastructure needs to be distributed across the entire bus service region to support a wirelessly charged transit bus fleet. Thus, it is useful to quantify the trade-offs of infrastructure-related costs and battery-associated savings to explore the potential advantages of wireless charging over plug-in charging.

Life cycle cost analysis (LCCA) is a useful tool to provide a holistic evaluation of costs from capital investment to use-phase operation and, finally, to the end of life (EoL) [11]. LCCA is widely used by transit agencies to evaluate cost benefits of fleet procurement plans. The U.S. Federal Transit Administration conducted an LCCA to compare costs of a conventional diesel bus fleet, hybrid bus fleet, and compressed natural gas bus fleet [12]. The Ann Arbor Area Transportation Authority (AAATA) also commissioned an LCCA comparing a conventional diesel bus fleet with a diesel hybrid bus fleet [13]. Although economic analysis of wireless charging has been reported in the literature [4], analysis of the trade-offs of wireless charging systems is limited, and a comprehensive LCCA comparing plug-in charging versus wireless charging bus fleet has not been established.

An integrated life cycle assessment and life cycle cost (LCA-LCC) model [11, 14] was developed to provide a comprehensive assessment and comparison of plug-in charging and wireless charging for an all-electric bus system. Such a comprehensive LCA-LCC model framework for evaluating the sustainability performance of this emerging wireless charging technology has not yet been established in the literature. This current study builds upon a previously conducted LCA comparing global warming impact and cumulative energy demand for the plug-in and wireless charging systems [15]. The LCA model was developed based on a simulation of an existing transit bus system serving the Ann Arbor and Ypsilanti metro area in Michigan. Parameters and intermediate results from the LCA and bus system simulation were used as input parameters for the LCCA. An advantage of this integrated LCA-LCC model is the ability to conduct energy, GHG emissions, and cost analyses simultaneously. For example, this model can be used to evaluate the magnitude of the environmental costs of carbon emissions and compare them with conventional LCCs.

In this study, a detailed cost analysis was conducted to compare the cumulative costs and total costs per bus-kilometer (km) between the plug-in and wireless bus systems. The results were also contrasted against a conventional pure diesel bus fleet and a diesel hybrid bus fleet for reference. Uncertainties associated with the results were evaluated by a Monte Carlo simulation. The relative importance of the key parameters influencing the LCCs of plug-in and wireless charging systems was identified by a sensitivity analysis. Finally, scenario analyses of EoL battery recycling, carbon emission costs, and different discount rates were conducted. This chapter demonstrates the trade-offs between plug-in and wireless charging and supplements current research on wireless charging technology through a detailed LCA-LCC evaluation.

3.2 Method

An integrated LCA-LCC model was developed to provide a comprehensive comparative assessment of plug-in charging and wireless charging with application for an electric bus fleet. The model framework is shown in Figure 3.1, and the LCA and LCC models are described in the sections below.

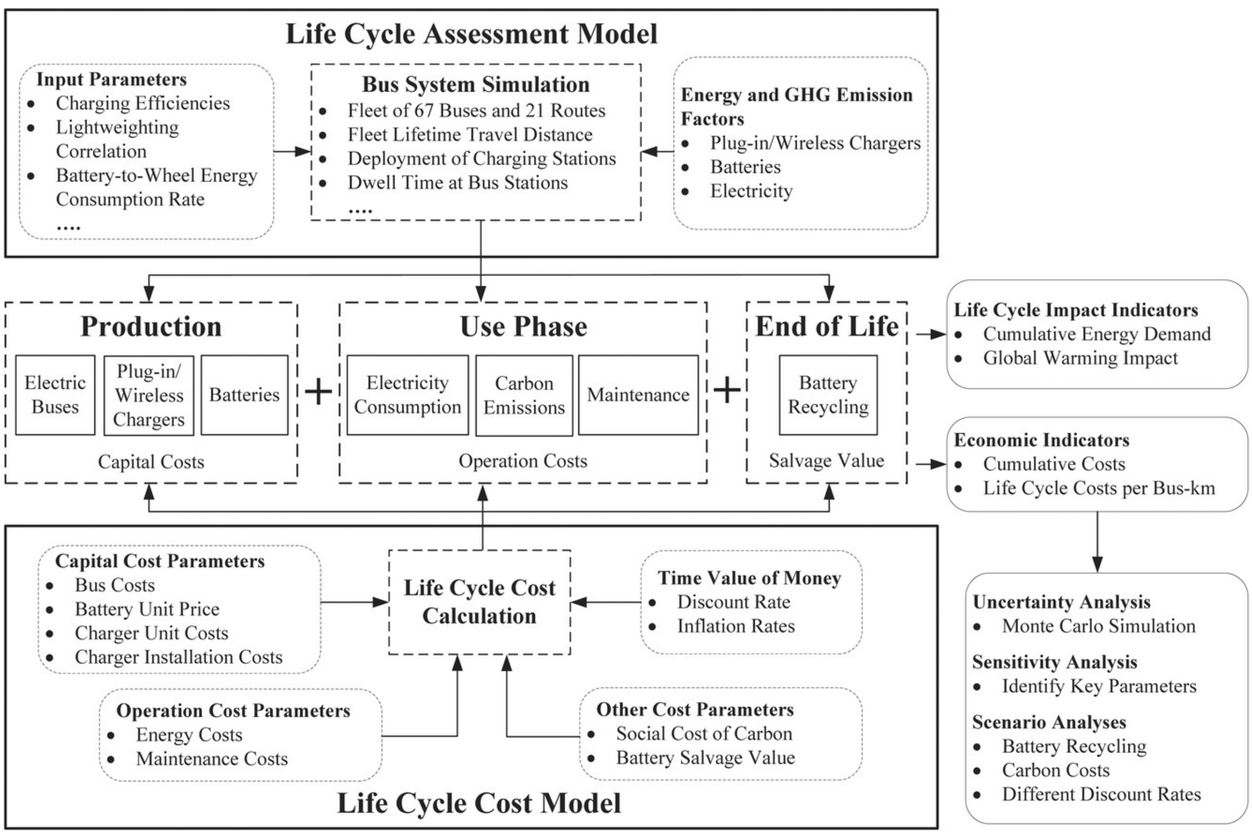


Figure 3.1 Integrated life cycle assessment and life cycle cost (LCA-LCC) model for comparative assessment of plug-in versus wireless charging systems with key parameters highlighted. The production of electric buses (excluding the batteries), use-phase maintenance, and battery recycling are only relevant to the LCC model

3.2.1 The Life Cycle Assessment Model and Bus System Simulation

The LCA model was constructed to simulate a bus fleet of 67 buses. The bus system in Ann Arbor-Ypsilanti metro area in Michigan, called TheRide, was used as a basis for the bus system simulation [16]. The main characteristics of this bus system, including fleet lifetime travel distance, dwell time at bus stops, distribution of routes, and bus stops, were used as parameters for the simulation. The rationale of selecting this bus system as a case study is that it is familiar to the modelers and route data were readily accessible. It is a typical multi-route system serving two major municipalities, Ann Arbor and Ypsilanti, and this simulation can be generalized and extended to other bus systems by tuning those characteristic parameters for a bus system. Bus systems with greater overlapping routes would be expected to require fewer total number of charging stations and would help increase the utilization of each charging station, and bus systems with longer dwell time at charging stations would help further downsize the onboard battery. The bus service life was assumed to be 12 years [12], and, on average, each bus traveled 716,932 km during that period [15]. The buses in this fleet are all assumed to be pure electric buses for which two charging scenarios were compared: plug-in charging and wireless charging. Major differences between the two bus systems using either charging method are highlighted, including chargers, batteries, and use-phase energy consumption. Sixty-seven plug-in chargers were assumed to be located at a parking lot for all-electric buses to charge overnight only, that is, no daytime charging. For the wireless charging scenario, 67 on-board wireless chargers (on-WCs) were installed on the buses and 428 off-board wireless chargers (off-WCs) were assumed to be deployed across the bus service region and located at transit centers, key downtown bus stops, some suburban bus stops, and a parking lot for buses to charge both day and night. Major input parameters used in the LCA model are listed in Table 3.1. Further details on the parameters and assumptions of the bus system simulation can be found in the Appendix.

Table 3.1 Main input parameters of the life cycle assessment model

Parameter	Value	Unit	References	Note
Life of a bus	12	years	[12]	
Life of a plug-in or wireless charger	24	years	[15, 17]	Techno-economic life
Weight of a plug-in charged bus	15000	kg	[18, 19]	Included 1,000 kg of passengers, driver and cargo
Battery-to-wheel energy consumption rate of a plug-in all-electric bus	1.46	kWh/km	[18]	Average of several real road tests
Lightweighting correlation	4.5%	percent	[15]	Percentage of battery-to-wheel energy consumption reduction per 10% bus mass reduction
Plug-in charging efficiency	90%	percent	[20]	Grid to battery
Wireless charging efficiency	85%	percent	[5, 21-23]	Grid to battery
Charger power	60	kW	[18]	Plug-in and wireless chargers have the same power rate.
Battery charge/discharge efficiency	90%	percent	[24, 25]	Energy discharged from battery divided by energy charged into battery
SOC range (SOCR)	60%	percent	[26]	The battery state of charge window
Battery cycle life	3000	cycles	[20, 24, 27]	
Battery specific energy	0.13	kWh/kg	[28]	Battery chemistry of lithium manganese oxide (LMO)

Note: SOC = state of charge; kg = kilograms; kWh/km = kilowatt-hours per kilometer; kW = kilowatts; kWh/kg = kilowatt-hours per kilogram.

3.2.2 The Life Cycle Cost Model

Results from the LCA model were used as input parameters in the LCC model. The LCA model quantified the battery sizes for plug-in buses and wireless buses. A plug-in battery was assumed to be 3,525 kilograms (kg) (458 kilowatt-hours [kWh]) with a battery-to-wheel energy consumption rate of 1.46 kWh/km. A wireless battery size can be downsized to 948 to 1,546 kg (123 to 201 kWh) with a battery-to-wheel energy consumption rate of 1.36 to 1.38 kWh/km, depending on the distance of the route and available charging time [15]. Use-phase energy consumption was also computed in the LCA model based on fleet travel distance. Using the U.S. annual carbon dioxide (CO_2) total output emission rate (0.559 kg CO_2/kWh) from the Emissions & Generation Resource Integrated Database (eGRID) database [29], the CO_2 emissions in the use phase were calculated and then used for the scenario analysis of carbon emission costs in the LCC model.

The time horizon for the LCC model is 24 years, that is, twice the life of a bus and the same as the techno-economic life of the charging infrastructure. In addition to plug-in and wireless charging all-electric bus systems, conventional diesel bus and diesel hybrid bus systems were also included in the LCC model so that the results can be contrasted for reference. Common cost parameters shared by the four systems are summarized in Table 3.2 and specific cost parameters for each system are listed in Table 3.3 and classified as capital and operation costs. The LCC model also considered the inflation or deflation of products and the discount rate.

Table 3.2 General cost parameters for the life cycle cost analysis

Name	Value	Unit	References
Unit price of battery pack	500	$/kWh	[30-32]
Electricity rate in Michigan (day & night)	0.1137	$/kWh	[33]
Diesel price	3.14	$/gal	[13]
Fuel economy of a conventional diesel bus	4.3	miles/gal	[13]
Fuel economy of a hybrid bus	5.3	miles/gal	[13]
Discount rate (20-year, nominal)	3.6%	percent	[34]
Annual inflation rate of lithium-ion battery	–9%	percent	[32, 35, 36]
Annual inflation rate of electricity rate	2%	percent	[37, 38]
Annual inflation rate of diesel	5.84%	percent	[37, 38]

Note: A negative inflation rate means the price is actually deflating. $/kWh=dollars per kilowatt-hour; $/gal = dollars per gallon; miles/gal = miles per gallon.

Table 3.3 Cost parameters and intermediate calculated values for life cycle cost analysis

Name	Unit	Plug-in	References	Wireless	References	Conventional	References	Hybrid	References
Capital costs									
Procurement of a bus (w/o battery)	$	500000	[39]	500000	Assumption	455298	[13]	615763	[13]
Procurement of a battery pack (average)	$	229125	Calculated	91192	Calculated	—	—	35000	[13]
Procurement of a plug-in charger (60 kW)	$	8000	[39]	—	—	—	—	—	—
Procurement of an onboard wireless charger (60 kW)	$	—	—	5000	[17]	—	—	—	—
Procurement of an off-board wireless charger (60 kW)	$	—	—	5000	[17]	—	—	—	—
Installation of a charger	$	1000	Assumption	10000	[17]	—	—	—	—
Operation costs									
Energy: electricity (day)	$/fleet/year	—	—	473101	Calculated	—	—	—	—
Energy: electricity (overnight)	$/fleet/year	820475	Calculated	345608	Calculated	—	—	—	—
Energy: diesel	$/fleet/year	—	—	—	—	1816283	Calculated	1473588	Calculated
Maintenance of facility & infrastructure	$/fleet/year	100000	Assumption	100000	Assumption	114746	[12, 13]	97159	[12, 13]
Maintenance of propulsion	$/fleet/year	352638	Assumption	352638	Assumption	362234	[12, 13]	352638	[12, 13]

Note: kW = kilowatts; fleet = 67 buses.

3.2.2.1 Capital Costs

Capital costs include bus and battery procurement, charger procurement, and installation of chargers. Batteries were assumed to be replaced every 8 years, and buses (excluding the batteries) were assumed to be replaced every 12 years [12, 15]. Batteries' costs were calculated from multiplying battery unit price ($/kWh) [1] by the battery capacities (kWh). The battery capacities were quantified so that they can meet daily range requirements and have enough capacity buffer to accommodate future capacity degradation. Details of battery sizing can be found in the LCA model [15]. A 60-kilowatt (kW) wireless charger is comprised of an on-board portion (on-WC) and an off-board portion (off-WC) that have an identical unit price of US$5,000 each. The market price for a 60-kW wireless charger and its installation costs, including pavement removal and restoration, were based on empirical and expert estimates [17], and further sensitivity analysis was conducted on these parameters.

3.2.2.2 Operation Costs

Operation costs include energy costs and maintenance costs. Operation costs were assumed to be paid at the end of each year. Other use-phase costs, including driver wages and vehicle insurance/warranty, were assumed to be the same for all four bus systems, thus not included in the comparison. Federal subsidies for purchasing buses by municipalities were not considered. The additional operation costs incurred by a decrease in battery charge/discharge efficiency resulting from battery degradation were assumed to be the same for both plug-in and wireless systems, but the methods can be refined to incorporate a specific battery efficiency and degradation profile for wireless charging. Additionally, although regenerative braking was included in terms of quantifying energy performance of the electrified buses in this study, its potential benefit of reducing the wear of the brake pad and cutting the maintenance costs of brake components [40] was not included.

For plug-in and wireless systems, use-phase electricity E (kWh) was calculated based on the battery-to-wheel energy consumption rate k (kWh/km), charging efficiency η_c (%), battery charge/discharge efficiency η_b (%), and fleet travel distance D (km), as shown in Eq. 3.1. Similarly, for conventional pure diesel and hybrid buses, diesel consumption was calculated from dividing fleet travel distance by fuel economy.

$$E = k \times D / \eta_{\mathrm{b}} / \eta_{\mathrm{c}} \qquad \text{(Eq. 3.1)}$$

Annual maintenance costs are comprised of two parts: maintenance of facilities and infrastructure and maintenance of vehicle propulsion or powertrain systems. As shown in Table 3.3, the maintenance costs of conventional pure diesel and hybrid buses were obtained and calculated from the literature. Because of lack of specific data on the maintenance costs of plug-in charging and wireless charging, three assumptions were made: (1) The propulsion maintenance costs of plug-in and wireless charging electric buses were assumed to be the same as the hybrid buses ($352,638/fleet/year); (2) the annual maintenance cost of 428 off-board wireless chargers [15] deployed across the bus service area is around 5% of their total procurement cost; and (3) a wireless charger will have the same rate of degradation as a plug-in charger during operation. The assumptions on the maintenance costs of plug-in and wireless chargers were further examined in the sensitivity analysis.

3.2.2.3 End-of-Life Battery Salvage Value

For the base case, the battery recycling was not considered, but it was considered in a scenario analysis. The threshold for battery retirement is usually a 20% loss of battery capacity [27, 41], that is, 80% of the nameplate capacity is still usable. Given the large capacity of a plug-in or wireless battery, it is meaningful to reuse the battery for other energy storage purposes. The scenario analysis was based on a battery salvage value varying from $0 to $400 per kWh of nameplate capacity. A 20% loss of battery usable capacity at EoL is assumed to reduce the original battery unit price (500/kWh) by 20%, thus the upper limit of battery salvage value is $400 per kWh of nameplate capacity. The battery recycling price was assumed to have the same annual inflation rate as the battery unit price (-9.00%).

3.2.2.4 Carbon Emission Costs

Another scenario analysis examined carbon emission costs. In the base case, no carbon costs were included. In the scenario analysis, however, the carbon emissions from diesel combustion or electricity generation during the use phase were assumed to be charged at a carbon price ranging from 0 to 100 $/tonne (t) CO_2,[2] based on the social cost of carbon [42].

3.3 Results and Discussion

3.3.1 Cumulative and Total Costs

Model results are reported as cumulative costs on a year-to-year basis and also cost per bus-km basis. Figure 3.2 shows the cumulative costs of plug-in all-electric, wireless all-electric, conventional pure diesel, and hybrid bus systems. At the beginning of the time horizon (year 0), the plug-in system has the highest capital cost and conventional pure diesel system has the lowest capital cost. At the end of the 24th year, the hybrid system has the highest costs over the period with a final life cycle cost of US$125.6 million. The wireless system is found to be the lowest with a final life cycle cost of US$94.7 million. Plug-in system has a final life cycle cost of US$102.2 million, which is US$115.6 million. Conventional and hybrid buses are powered solely by diesel, and plug-in or wireless buses are powered solely by electricity. The alternative powertrains have better energy efficiencies compared to conventional powertrains [43]. Thus, the differences in fuel type and fuel economy result in different fueling cost increases per year, reflected in the slopes of the curves. At the 8th and 16th years, there are scheduled battery replacements for all-electric and hybrid buses, and at the 12th year, there is a bus replacement for all types of buses (except the batteries). The plug-in battery has around 2.5 times the capacity of the wireless battery, thus it costs more to replace a plug-in battery. The battery replacement plays an important role in determining the difference between the plug-in system and the wireless system.

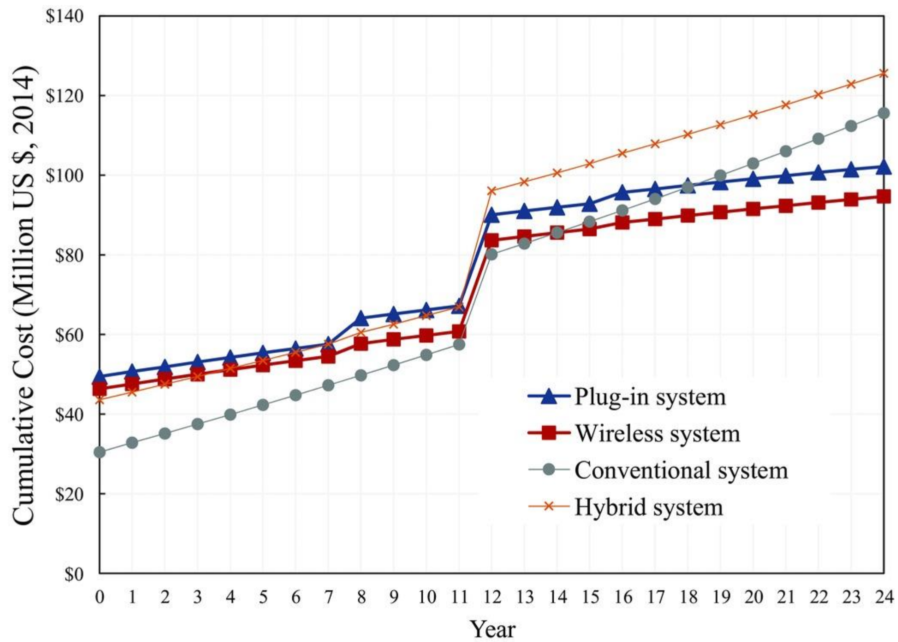
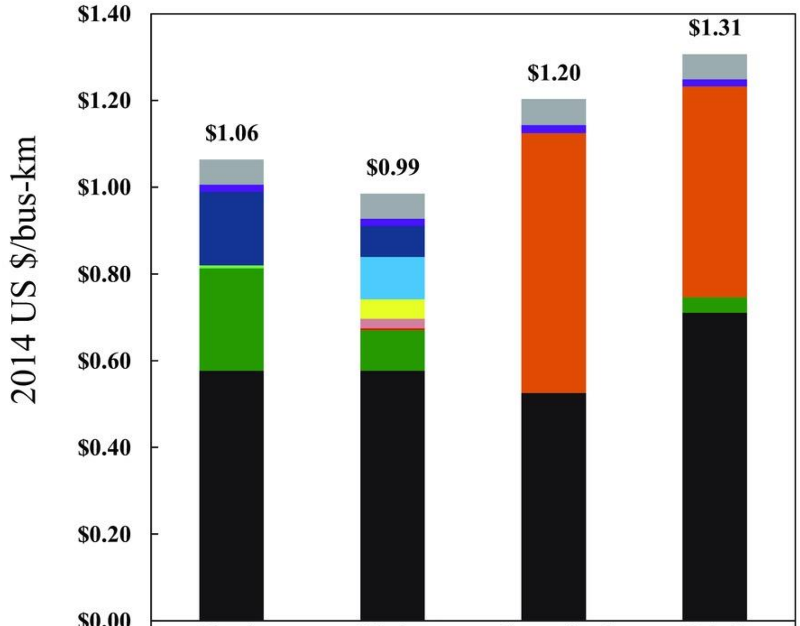


Figure 3.2 Cumulative costs of plug-in all-electric, wireless all-electric, conventional pure diesel, and diesel hybrid bus systems

A detailed breakdown of the total life cycle costs per bus-km of the four systems is shown in Figure 3.3. The hybrid, conventional, plug-in, and wireless systems cost US$1.31, US$1.20, US$1.06, and US$0.99 per bus-km, respectively. Trade-offs between plug-in and wireless systems are compared directly against each other. One major advantage of wireless charging is the lower battery costs, including initial procurement and use-phase replacements. Wireless batteries cost 60% less than plug-in batteries, but there are increased infrastructure costs for wireless charging, including procurement and installation of chargers. The infrastructure costs only 0.7 cent per bus-km for plug-in charging, but increases to 7 cents per bus-km for wireless charging. In terms of use-phase electricity consumption, the two systems have almost the same electricity costs. The reason is that, though there is a lightweighting benefit of battery-to-wheel energy consumption reduction of approximately 5.4% to 7.0%, the wireless charging efficiency was assumed to be 85%, which is less than the assumed plug-in charging efficiency of 90%. The lightweighting benefit is offset by the difference in charging efficiencies, thus the difference found in final electricity costs between the plug-in and wireless systems is small.



	Plug-in	Wireless	Conventional	Hybrid
Maintenance - propulsion	$0.058	$0.058	$0.060	$0.058
Maintenance - facility & infrastructure	$0.017	$0.017	$0.019	$0.016
Diesel	-	-	$0.599	$0.486
Electricity (night)	$0.170	$0.071	-	-
Electricity (day)	-	$0.098	-	-
Charger installation	$0.001	$0.045	-	-
Offboard wireless chargers	-	$0.022	-	-
Onboard wireless chargers	-	$0.003	-	-
Plug-in chargers	$0.006	-	-	-
Battery packs	$0.236	$0.094	-	$0.036
Buses (w/o batteries)	$0.577	$0.577	$0.525	$0.710
Total	$1.06	$0.99	$1.20	$1.31

Figure 3.3 Total costs per bus-km of plug-in all-electric, wireless all-electric, conventional pure diesel, and diesel hybrid bus systems. km = kilometer

3.3.2 Uncertainty Analysis

Wireless charging has not been commercialized in a large scale. Thus, in this model, many parameter values were based on assumptions. These uncertain parameters are listed in the Appendix, along with their respective possible ranges. An uncertainty analysis using a Monte Carlo simulation [44] was conducted based on these ranges, assuming a triangular distribution of low, most likely, and high values for each parameter. The Monte Carlo simulation was run with 20,000 trial times, and each time the parameter values were changed stochastically based on their respective ranges and distributions. The simulation results are reported in the Appendix, showing the minimum, first quartile, median, third quartile, and maximum of the trial results for each bus system. Among the four systems, the wireless system has the lowest median of US$0.99/bus-km and the hybrid system has the highest median of US$1.31/bus-km. In terms of minimum and maximum, the wireless system could have the lowest possible cost of US$0.81 per bus-km and the hybrid system could have the highest possible cost of US$1.63 per bus-km.

3.3.3 Sensitivity Analysis

To evaluate the individual contribution of key parameters to the overall uncertainty, a sensitivity analysis was conducted. In the sensitivity analysis, each parameter was changed independently, based on the same range defined for the Monte Carlo simulation. The results of sensitivity analysis are summarized in Figure 3.4. The tornado graph ranks parameters according to their contribution to the difference between the plug-in system and wireless system. The initial unit price of battery pack ($/kWh) is an important parameter in determining the difference between the two systems. The wireless charging system has an advantage in terms of battery size reduction. If the battery unit price is lower, however, this advantage of wireless charging will be smaller. If the initial battery price is US$300/kWh, the wireless charging system will cost only 2.2% less than the plug-in charging system. If the battery unit price starts at US$700/kWh, the wireless charging system will cost around 9.5% less than the plug-in system. The day and night electricity prices were also identified as important parameters, but they each affect the difference in an opposite way. Either a lower daytime electricity rate or a higher nighttime electricity rate will make wireless charging more advantageous. This is because for wireless charging, 58% of the use-phase electricity consumption is charged during bus operation and 42% is charged overnight, but for plug-in charged buses, they were assumed to be charged only overnight. Finally, the result is also sensitive to the changes in installation cost of off-WCs and wireless charging efficiency, but the result is less sensitive to the procurement cost of off-WC, maintenance costs of plug-in and wireless chargers, time of charging at each transit center, inflation rate of lithium-ion battery, lightweighting correlation, and procurement of on-board wireless charger.

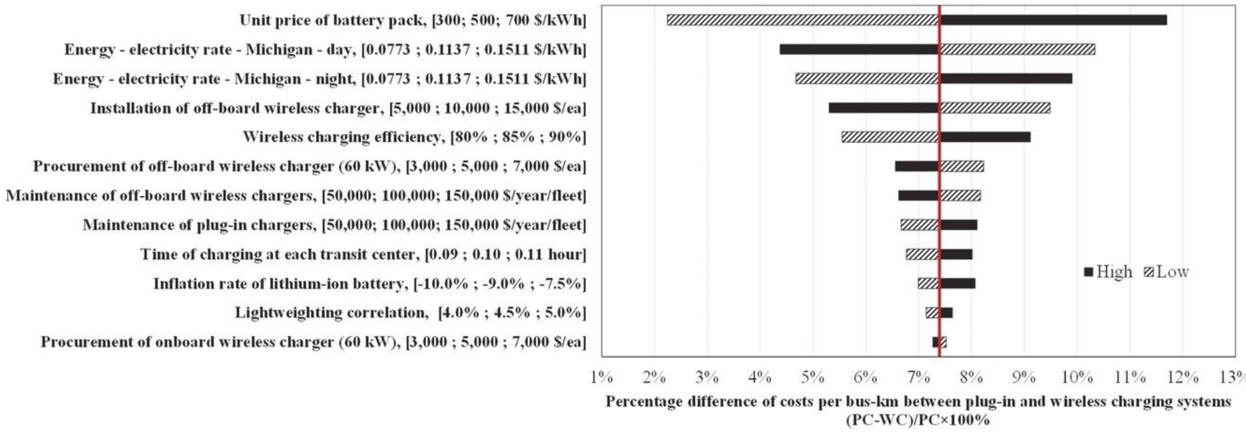


Figure 3.4 Sensitivity analysis. Each input parameter is changed independently from values of “low; base; high” as shown beside each parameter's name. The base case (7.4%) is shown as the red line

3.3.4 Scenario Analyses

Three scenario analyses were conducted to evaluate the (1) potential benefits of recycling the large on-board batteries for electric buses, (2) external cost of carbon emissions, and (3) uncertainty in discount rate, and results are shown in Figure 3.5. The plug-in charged bus has a battery with a capacity of 458 kWh, and the wireless bus has a battery with a capacity of 123 to 201 kWh. These batteries have a potential of being recycled after retirement. As shown in Figure 3.5, a battery salvage value was applied, with US$0 per nameplate kWh as the most pessimistic scenario and US$400 per nameplate kWh as the most optimistic scenario. When a battery is recycled at a price of US$400 per nameplate kWh, the wireless and plug-in charging systems will have very similar costs per bus-km.

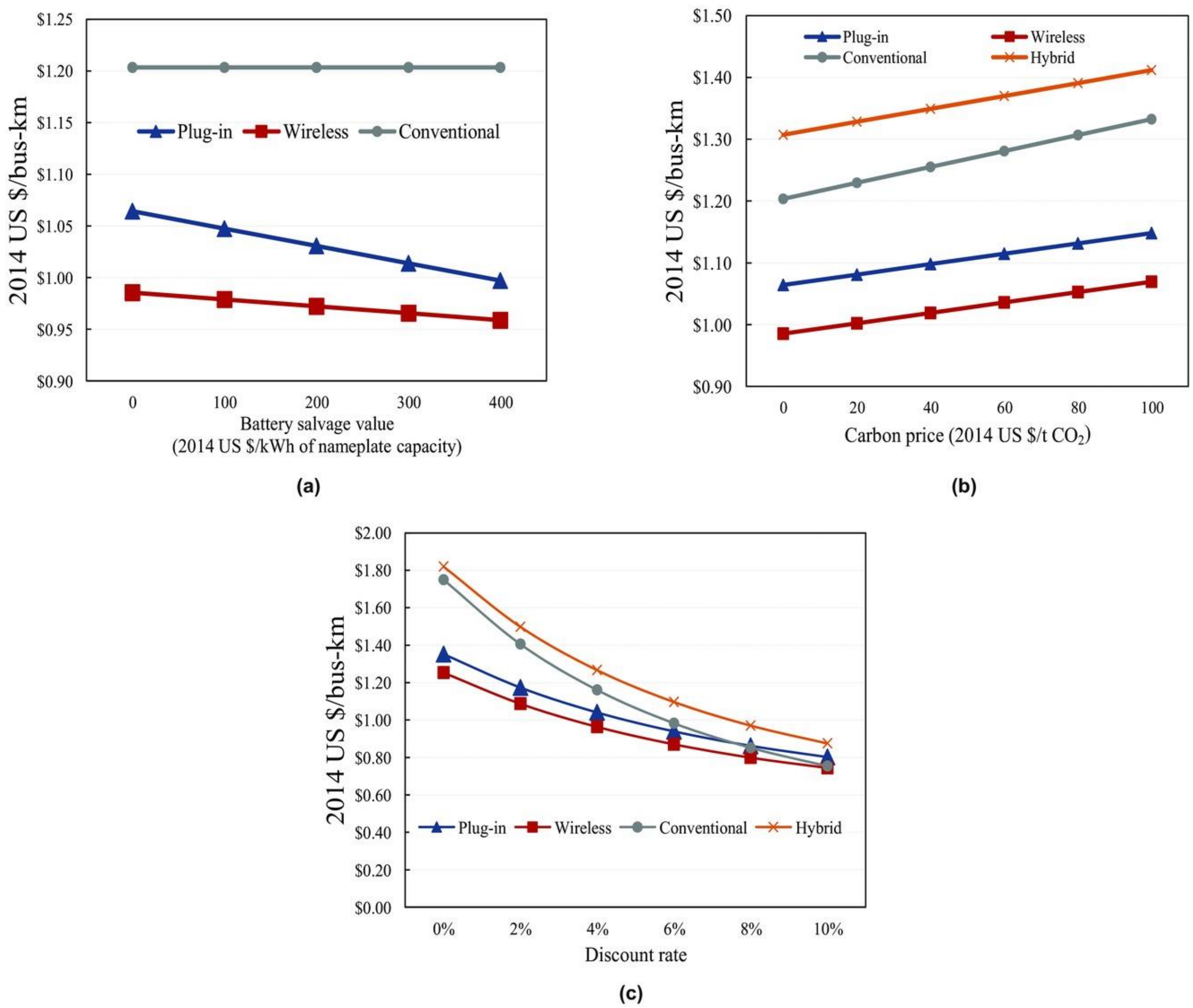


Figure 3.5 Scenario analyses: (a) end-of-life battery recycling; (b) carbon costs; and (c) discount rate

A carbon emission price, ranging from US$0 to US$100 per tonne of CO_2, was placed on the use-phase carbon emissions of the four systems, either from the combustion of diesel or the generation of electricity, as shown in Figure 3.5. From US$0 to US$100/t CO_2, the cost per bus-km increases by 8.0% (US$0.10) for the hybrid system, 10.7% (US$0.13) for the conventional pure diesel system, 7.9% (US$0.08) for the plug-in system, and 8.5% (US$0.08) for the wireless system. The difference between the conventional and hybrid systems is mainly attributable to the difference in fuel economies. The reason for the same price increases of plug-in and wireless systems is that the lightweighting benefit is offset by lower wireless charging efficiency.

The choice of discount rate is somewhat subjective in LCCA, thus a scenario analysis using different discount rates was conducted, as shown in Figure 3.5. At a high discount rate of 10%, the difference among the four systems is much smaller than that at a discount rate of 0%. The conventional system is more affected by the change in discount rate because of greater use-phase costs. A large portion of cost for conventional system is the diesel cost. When the discount rate is higher, the fuel cost is lower at present value. Thus, discount rate affects the conventional system more than the other three systems.

3.4 Conclusion

The model was used to evaluate the trade-offs of utilizing wireless charging technology for an electric bus system. Deploying wireless chargers for an all-electric bus system has benefits of downsizing the battery and reducing the battery and use-phase electricity costs. In contrast, the wireless charging infrastructure brings additional costs of charger procurement and installation. Though this study indicates that a wireless charging system has a lower overall LCC compared to a plug-in charging system, there is considerable uncertainty associated with this finding. The difference in LCCs between plug-in charging and wireless charging is largely dependent on the battery unit price, wireless charging efficiency, and procurement, installation, and maintenance costs of wireless chargers. If any of these parameters changes significantly in the future, it will greatly affect the relative cost differences between the two charging methods. For example, if the wireless charging efficiency is improved, it will further help reduce the LCC of the wireless charging bus system. Also, after initial commercialization, the mass production and economy of scale benefits are expected to decrease wireless charger costs as the market matures.

Future studies can incorporate and extend a recently established optimization method [45] to screen the best candidate bus stops for installation of charging infrastructure and quantify the optimal battery sizes to minimize LCC of a wireless charging bus system. The established optimization study was based on a single route in Korea to allocate the charging infrastructure for the least total cost of battery and infrastructure only. To extend the method, the optimization algorithm needs to consider the characteristics of a network of different bus routes, such as the sharing of a single charging station by multiple routes. The utilization of a charging station may also affect the life and maintenance cost of the charging infrastructure. The charge/discharge frequency and state of charge pattern may also have an impact on battery degradation, which would affect the frequency of battery replacement and battery cost [46]. Therefore, it can be meaningful to explore the optimal deployment of off-WCs and consider the infrastructure utilization rate and battery degradation to minimize life cycle energy consumption, GHG emissions, or costs. The trade-off of charging infrastructure and battery size also needs to be further explored by extending the model to incorporate dynamic wireless charging. With more charging infrastructure available and charging in motion, a wirelessly charged bus can carry a further downsized on-board battery [21, 47]. It will be useful to analyze whether the marginal benefit of further battery downsizing will offset the marginal burdens from increased wireless charging infrastructure.

Notes

1. Throughout the chapter and Appendix, all dollar values presented are in U.S. dollars.

2. Throughout the chapter and Appendix, "t" refers to metric tons.

Appendix A Supporting information for Chapter 3

The appendix contains additional background information on the bus system simulation that was based on the transit bus fleet operating in Ann Arbor and Ypsilanti area in Michigan, U.S.A. The detailed calculation and results of life cycle costs comparing the plug-in all-electric, wireless all-electric, conventional pure diesel and diesel hybrid bus systems are also provided.

Bus System Simulation

The integrated life cycle assessment and life cycle cost (LCA-LCC) model was based on a bus system simulation using the Ann Arbor and Ypsilanti area bus fleet as a case study [16]. The adapted bus system map is shown in Figure 3.6. Detailed parameters are summarized in Table 3.4 and Table 3.5 [15]. The simulation was a simplification of the real bus system and several assumptions were made to facilitate modeling, including:

- Twenty-one routes were modeled and classified into three groups: the blue, red and green routes. Thirteen blue routes operate around Ann Arbor, four red routes operate between Ann Arbor and Ypsilanti, and four green routes operate near Ypsilanti.
- Altogether 67 buses were modeled.
- Buses in the same group were assumed to operate in the same manner, including the same range traveled, the same dwell time at bus stops and the same size of battery.
- Ann Arbor and Ypsilanti downtown areas were assumed to be the areas illustrated as the white boxes shown in Figure 3.6, where multiple routes can share a same bus stop. However, a suburban bus stop was assumed to be used by a single route exclusively.
- At the Ann Arbor's Blake Transit Center (BTC) and the Ypsilanti Transit Center (YTC), buses were assumed to stay as long as 6 minutes.
- Approximately 25% of the bus operation time was assumed to be the dwell time at bus stops and transit centers [48].
- The onboard wireless charging coil weight (order of magnitude of kilograms) is assumed to be negligible compared to the battery downsizing (order of magnitude of metric tonne). Therefore, the impact of additional charging coil weight is not considered in this model but can be incorporated in future work for a more sophisticated model.

Based on the bus system simulation described above, four hypothesized scenarios were compared:

1) Plug-in charging all-electric bus fleet: There assumed to be 67 plug-in chargers located at a parking lot for buses to charge overnight only, that is to say no charging during operation at bus stops and transit centers.
2) Wireless charging all-electric bus fleet: Off-board wireless chargers (off-WCs) were assumed to be located at transit centers, some bus stops as well as a parking lot to allow buses to charge both overnight and during operation. Altogether 428 off-WCs were assumed to be distributed across the Ann Arbor and Ypsilanti area.
3) Conventional pure diesel bus fleet and 4) diesel hybrid bus fleet: Buses in these two scenarios were assumed to be fueled by existing pumps, thus no additional costs of fueling facilities were accounted.

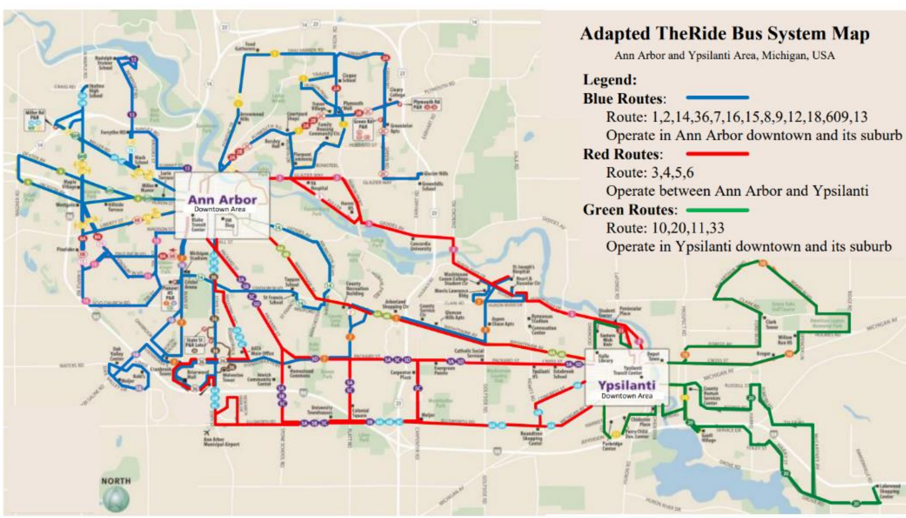


Figure 3.6 Adapted TheRide bus system map, based on the bus system map from the Ann Arbor Area Transportation Authority [16]

Table 3.4 Bus system simulation: route details

	Route Details (Downtown + Suburb)							Suburb Details		
Route Group	How many routes	miles/ loop	stops/ loop	loops/ weekday	loops/ Sat or Sun	hour/ loop	buses/ route	stops (both directions)/ route	off-WCs (both directions)/ route	charging time (hour)
Blue	13	9 (= 14 km)	42	13	7	1	3	28	8	0.008
Red	4	13 (= 21 km)	64	9	5	1.5	4	32	10	0.008
Green	4	9 (= 14 km)	42	13	7	1	3	28	8	0.008

Note: Take the blue routes as an example. There are 13 blue routes, and each route has 3 buses. Each bus travels 9 miles (= 14 km) in each loop (round trip). One loop has 42 stops deployed and takes 1 hour. Each bus travels 13 loops on weekday and 7 loops on Saturday or Sunday. Of the 42 stops in each loop, 28 stops are in suburb and 8 stops out of those 28 stops are equipped with off-board wireless chargers (off-WCs). In suburb, the bus charges 0.008 hour at each off-WC.

Table 3.5 Bus system simulation: details of downtown, transit centers and parking lot

Downtown Details	Ann Arbor downtown		Ypsilanti downtown		
Number of bus stops	160		80		
Number of off-WCs	80		40		
Time of charging/charging stop (hour)	0.01		0.01		
Transit Center Details					
	BTC	CCTC	Hospital	Union	YTC
Number of off-WCs	10	4	4	2	6
Time of charging (hour)	0.1	0.01	0.01	0.01	0.1
Parking Lot Details					
Number of plug-in chargers	67				
Number of off-WCs	67				

Note: BTC = Blake Transit Center; CCTC = Central Campus Transit Center; YTC = Ypsilanti Transit Center.

Life Cycle Cost Calculation

Table 3.6 Life cycle cost calculation: plug-in charging all-electric bus system (unit: U.S. $)

		Capital Costs						Operation Costs					Total	Cumulative
Year	*Discount Factor*	*Buses (w/o batteries)*	*Battery packs*	*Plug-in chargers*	*Onboard wireless chargers*	*Offboard wireless chargers*	*Charger installation*	*Electricity (day)*	*Electricity (night)*	*Diesel*	*Maintenance - facility & infrastructure*	*Maintenance - propulsion*	*Total annual costs*	*Plug-in system*
0	1.00	33,500,000	15,351,375	536,000	0	0	67,000	0	0	0	0	0	49,454,375	49,454,375
1	0.97		0	0	0	0	0	0	836,885	0	100,000	352,638	1,244,714	50,699,089
2	0.93	0	0	0	0	0	0	0	853,623	0	100,000	352,638	1,217,056	51,916,144
3	0.90	0	0	0	0	0	0	0	870,695	0	100,000	352,638	1,190,118	53,106,262
4	0.87	0	0	0	0	0	0	0	888,109	0	100,000	352,638	1,163,879	54,270,141
5	0.84	0	0	0	0	0	0	0	905,871	0	100,000	352,638	1,138,319	55,408,460
6	0.81	0	0	0	0	0	0	0	923,989	0	100,000	352,638	1,113,417	56,521,877
7	0.78	0	0	0	0	0	0	0	942,468	0	100,000	352,638	1,089,154	57,611,031
8	0.75	0	7,219,023	0	0	0	0	0	961,318	0	100,000	352,638	6,505,529	64,116,560
9	0.73	0	0	0	0	0	0	0	980,544	0	100,000	352,638	1,042,470	65,159,030
10	0.70	0	0	0	0	0	0	0	1,000,155	0	100,000	352,638	1,020,014	66,179,045
11	0.68	0	0	0	0	0	0	0	1,020,158	0	100,000	352,638	998,126	67,177,171
12	0.65	33,500,000	0	0	0	0	0	0	1,040,561	0	100,000	352,638	22,891,096	90,068,267
13	0.63	0	0	0	0	0	0	0	1,061,373	0	100,000	352,638	955,987	91,024,254
14	0.61	0	0	0	0	0	0	0	1,082,600	0	100,000	352,638	935,706	91,959,960
15	0.59	0	0	0	0	0	0	0	1,104,252	0	100,000	352,638	915,929	92,875,888
16	0.57	0	3,394,764	0	0	0	0	0	1,126,337	0	100,000	352,638	2,824,405	95,700,293
17	0.55	0	0	0	0	0	0	0	1,148,864	0	100,000	352,638	877,832	96,578,125
18	0.53	0	0	0	0	0	0	0	1,171,841	0	100,000	352,638	859,486	97,437,611
19	0.51	0	0	0	0	0	0	0	1,195,278	0	100,000	352,638	841,588	98,279,199
20	0.49	0	0	0	0	0	0	0	1,219,183	0	100,000	352,638	824,128	99,103,328
21	0.48	0	0	0	0	0	0	0	1,243,567	0	100,000	352,638	807,093	99,910,421
22	0.46	0	0	0	0	0	0	0	1,268,438	0	100,000	352,638	790,470	100,700,891
23	0.44	0	0	0	0	0	0	0	1,293,807	0	100,000	352,638	774,249	101,475,140
24	0.43	0	0	0	0	0	0	0	1,319,683	0	100,000	352,638	758,418	**102,233,558**

Note: Total annual costs and cumulative costs were discounted to 2014 U.S. dollar.

Table 3.7 Life cycle cost calculation: wireless charging all-electric bus system (unit: U.S. $)

		Capital Costs						Operation Costs					Total	Cumulative
Year	*Discount Factor*	*Buses (w/o batteries)*	*Battery packs*	*Plug-in chargers*	*Onboard wireless chargers*	*Offboard wireless chargers*	*Charger installation*	*Electricity (day)*	*Electricity (night)*	*Diesel*	*Maintenance - facility & infrastructure*	*Maintenance - propulsion*	*Total annual costs*	*Wireless system*
0	1.00	33,500,000	6,109,847	0	335,000	2,140,000	4,280,000	0	0	0	0	0	46,364,847	46,364,847
1	0.97	0	0	0	0	0	0	482,563	352,520	0	100,000	352,638	1,242,974	47,607,820
2	0.93	0	0	0	0	0	0	492,214	359,570	0	100,000	352,638	1,215,343	48,823,163
3	0.90	0	0	0	0	0	0	502,058	366,762	0	100,000	352,638	1,188,431	50,011,594
4	0.87	0	0	0	0	0	0	512,099	374,097	0	100,000	352,638	1,162,219	51,173,813
5	0.84	0	0	0	0	0	0	522,341	381,579	0	100,000	352,638	1,136,684	52,310,497
6	0.81	0	0	0	0	0	0	532,788	389,210	0	100,000	352,638	1,111,807	53,422,304
7	0.78	0	0	0	0	0	0	543,444	396,995	0	100,000	352,638	1,087,569	54,509,873
8	0.75	0	2,873,171	0	0	0	0	554,313	404,934	0	100,000	352,638	3,229,078	57,738,951
9	0.73	0	0	0	0	0	0	565,399	413,033	0	100,000	352,638	1,040,934	58,779,885
10	0.70	0	0	0	0	0	0	576,707	421,294	0	100,000	352,638	1,018,502	59,798,387
11	0.68	0	0	0	0	0	0	588,241	429,720	0	100,000	352,638	996,637	60,795,024
12	0.65	33,500,000	0	0	0	0	0	600,006	438,314	0	100,000	352,638	22,889,630	83,684,654
13	0.63	0	0	0	0	0	0	612,006	447,080	0	100,000	352,638	954,544	84,639,198
14	0.61	0	0	0	0	0	0	624,246	456,022	0	100,000	352,638	934,284	85,573,482
15	0.59	0	0	0	0	0	0	636,731	465,142	0	100,000	352,638	914,530	86,488,012
16	0.57	0	1,351,116	0	0	0	0	649,466	474,445	0	100,000	352,638	1,662,514	88,150,526
17	0.55	0	0	0	0	0	0	662,455	483,934	0	100,000	352,638	876,476	89,027,002
18	0.53	0	0	0	0	0	0	675,704	493,613	0	100,000	352,638	858,150	89,885,152
19	0.51	0	0	0	0	0	0	689,218	503,485	0	100,000	352,638	840,274	90,725,426
20	0.49	0	0	0	0	0	0	703,003	513,555	0	100,000	352,638	822,834	91,548,260
21	0.48	0	0	0	0	0	0	717,063	523,826	0	100,000	352,638	805,819	92,354,078
22	0.46	0	0	0	0	0	0	731,404	534,302	0	100,000	352,638	789,216	93,143,294
23	0.44	0	0	0	0	0	0	746,032	544,988	0	100,000	352,638	773,014	93,916,308
24	0.43	0	0	0	0	0	0	760,953	555,888	0	100,000	352,638	757,201	**94,673,509**

Note: Total annual costs and cumulative costs were discounted to 2014 U.S. dollar.

Table 3.8 Life cycle cost calculation: conventional diesel bus system (unit: U.S. $)

		Capital Costs						**Operation Costs**					**Total**	**Cumulative**
Year	*Discount Factor*	*Buses (w/o batteries)*	*Battery packs*	*Plug-in chargers*	*Onboard wireless chargers*	*Offboard wireless chargers*	*Charger installation*	*Electricity (day)*	*Electricity (night)*	*Diesel*	*Maintenance - facility & infrastructure*	*Maintenance - propulsion*	*Total annual costs*	*Conventional system*
0	1.00	30,504,966	0	0	0	0	0	0	0	0	0	0	30,504,966	30,504,966
1	0.97	0	0	0	0	0	0	0	0	1,922,354	114,746	362,234	2,315,959	32,820,925
2	0.93	0	0	0	0	0	0	0	0	2,034,619	114,746	362,234	2,340,080	35,161,005
3	0.90	0	0	0	0	0	0	0	0	2,153,441	114,746	362,234	2,365,625	37,526,630
4	0.87	0	0	0	0	0	0	0	0	2,279,202	114,746	362,234	2,392,593	39,919,222
5	0.84	0	0	0	0	0	0	0	0	2,412,307	114,746	362,234	2,420,984	42,340,206
6	0.81	0	0	0	0	0	0	0	0	2,553,186	114,746	362,234	2,450,800	44,791,006
7	0.78	0	0	0	0	0	0	0	0	2,702,292	114,746	362,234	2,482,043	47,273,049
8	0.75	0	0	0	0	0	0	0	0	2,860,106	114,746	362,234	2,514,718	49,787,767
9	0.73	0	0	0	0	0	0	0	0	3,027,136	114,746	362,234	2,548,829	52,336,595
10	0.70	0	0	0	0	0	0	0	0	3,203,921	114,746	362,234	2,584,381	54,920,976
11	0.68	0	0	0	0	0	0	0	0	3,391,030	114,746	362,234	2,621,381	57,542,357
12	0.65	30,504,966	0	0	0	0	0	0	0	3,589,066	114,746	362,234	22,614,918	80,157,276
13	0.63	0	0	0	0	0	0	0	0	3,798,668	114,746	362,234	2,699,759	82,857,035
14	0.61	0	0	0	0	0	0	0	0	4,020,510	114,746	362,234	2,741,155	85,598,190
15	0.59	0	0	0	0	0	0	0	0	4,255,308	114,746	362,234	2,784,035	88,382,225
16	0.57	0	0	0	0	0	0	0	0	4,503,818	114,746	362,234	2,828,413	91,210,637
17	0.55	0	0	0	0	0	0	0	0	4,766,841	114,746	362,234	2,874,299	94,084,936
18	0.53	0	0	0	0	0	0	0	0	5,045,224	114,746	362,234	2,921,708	97,006,644
19	0.51	0	0	0	0	0	0	0	0	5,339,865	114,746	362,234	2,970,654	99,977,298
20	0.49	0	0	0	0	0	0	0	0	5,651,713	114,746	362,234	3,021,153	102,998,451
21	0.48	0	0	0	0	0	0	0	0	5,981,773	114,746	362,234	3,073,221	106,071,672
22	0.46	0	0	0	0	0	0	0	0	6,331,109	114,746	362,234	3,126,875	109,198,548
23	0.44	0	0	0	0	0	0	0	0	6,700,846	114,746	362,234	3,182,134	112,380,682
24	0.43	0	0	0	0	0	0	0	0	7,092,175	114,746	362,234	3,239,017	**115,619,699**

Note: Total annual costs and cumulative costs were discounted to 2014 U.S. dollar.

Table 3.9 Life cycle cost calculation: diesel hybrid bus system (unit: U.S. $)

		Capital Costs						**Operation Costs**					**Total**	**Cumulative**
Year	*Discount Factor*	*Buses (w/o batteries)*	*Battery packs*	*Plug-in chargers*	*Onboard wireless chargers*	*Offboard wireless chargers*	*Charger installation*	*Electricity (day)*	*Electricity (night)*	*Diesel*	*Maintenance - facility & infrastructure*	*Maintenance - propulsion*	*Total annual costs*	*Hybrid system*
0	1.00	41,256,121	2,345,000	0	0	0	0	0	0	0	0	0	43,601,121	43,601,121
1	0.97	0	0	0	0	0	0	0	0	1,559,646	97,159	352,638	1,939,616	45,540,737
2	0.93	0	0	0	0	0	0	0	0	1,650,729	97,159	352,638	1,957,080	47,497,817
3	0.90	0	0	0	0	0	0	0	0	1,747,131	97,159	352,638	1,975,771	49,473,588
4	0.87	0	0	0	0	0	0	0	0	1,849,164	97,159	352,638	1,995,687	51,469,275
5	0.84	0	0	0	0	0	0	0	0	1,957,155	97,159	352,638	2,016,827	53,486,102
6	0.81	0	0	0	0	0	0	0	0	2,071,453	97,159	352,638	2,039,188	55,525,291
7	0.78	0	0	0	0	0	0	0	0	2,192,426	97,159	352,638	2,062,771	57,588,062
8	0.75	0	1,102,742	0	0	0	0	0	0	2,320,463	97,159	352,638	2,918,567	60,506,629
9	0.73	0	0	0	0	0	0	0	0	2,455,979	97,159	352,638	2,113,607	62,620,236
10	0.70	0	0	0	0	0	0	0	0	2,599,408	97,159	352,638	2,140,864	64,761,100
11	0.68	0	0	0	0	0	0	0	0	2,751,213	97,159	352,638	2,169,350	66,930,450
12	0.65	41,256,121	0	0	0	0	0	0	0	2,911,884	97,159	352,638	29,187,111	96,117,561
13	0.63	0	0	0	0	0	0	0	0	3,081,938	97,159	352,638	2,230,033	98,347,594
14	0.61	0	0	0	0	0	0	0	0	3,261,923	97,159	352,638	2,262,240	100,609,834
15	0.59	0	0	0	0	0	0	0	0	3,452,419	97,159	352,638	2,295,699	102,905,533
16	0.57	0	518,567	0	0	0	0	0	0	3,654,041	97,159	352,638	2,624,895	105,530,428
17	0.55	0	0	0	0	0	0	0	0	3,867,437	97,159	352,638	2,366,408	107,896,836
18	0.53	0	0	0	0	0	0	0	0	4,093,295	97,159	352,638	2,403,676	110,300,512
19	0.51	0	0	0	0	0	0	0	0	4,332,343	97,159	352,638	2,442,232	112,742,744
20	0.49	0	0	0	0	0	0	0	0	4,585,352	97,159	352,638	2,482,088	115,224,833
21	0.48	0	0	0	0	0	0	0	0	4,853,137	97,159	352,638	2,523,256	117,748,089
22	0.46	0	0	0	0	0	0	0	0	5,136,560	97,159	352,638	2,565,748	120,313,837
23	0.44	0	0	0	0	0	0	0	0	5,436,535	97,159	352,638	2,609,579	122,923,416
24	0.43	0	0	0	0	0	0	0	0	5,754,029	97,159	352,638	2,654,761	**125,578,177**

Note: Total annual costs and cumulative costs were discounted to 2014 U.S. dollar.

Uncertainty Analysis and Monte Carlo Simulation

The probability distributions of major parameters for the Monte Carlo simulation are summarized in Table 3.10 and the result is shown in Figure 3.7. The low and high values of each parameter are based on literature data when available otherwise estimates based on our best judgement were used.

Table 3.10 Triangular probability distributions of major parameters for the Monte Carlo simulation (2014 U.S. $)

Parameter	Unit	Low	Most Likely	High	References and Notes
Unit price of battery pack	$/kWh	300	500	700	[30-32]
Energy - electricity rate - Michigan - day	$/kWh	0.0773	0.1137	0.1511	[33] Range and mean of all sectors in Michigan
Energy - electricity rate - Michigan - night	$/kWh	0.0773	0.1137	0.1511	[33] Range and mean of all sectors in Michigan
Procurement - all-electric bus (w/o battery)	$/bus (no battery)	450,000	500,000	550,000	[39]
Procurement - onboard wireless charger (60 kW)	$/ea	3,000	5,000	7,000	[17]
Procurement - off-board wireless charger (60 kW)	$/ea	3,000	5,000	7,000	[17]
Installation of plug-in charger	$/ea	500	1,000	1,500	Assumption
Installation of off-board wireless charger	$/ea	5,000	10,000	15,000	[17]
Maintenance of plug-in charger	$/year/fleet	50,000	100,000	150,000	Assumption
Maintenance of off-board wireless charger	$/year/fleet	50,000	100,000	150,000	Assumption
Discount rate	percent	1.60%	3.60%	5.60%	[34]
Annual inflation rate - lithium-ion battery	percent	-10.00%	-9.00%	-7.50%	[32, 35, 36]
Annual inflation rate of diesel price	percent	4.70%	5.80%	7.00%	[37, 38]
Wireless charging efficiency	percent	80%	85%	90%	[5, 21-23]
Lightweighting correlation	percent	4.00%	4.50%	5.00%	Assumption on percentage of battery-to-wheel energy consumption reduction per 10% bus mass reduction
Time of wireless charging per downtown charging station	hour	0.009	0.01	0.011	Assumption
Time of wireless charging per transit center	hour	0.09	0.1	0.11	Assumption

Note: a negative inflation rate means the price is actually deflating.

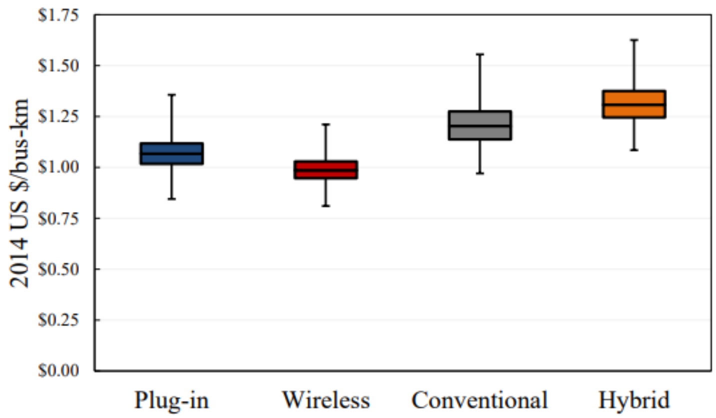


Figure 3.7 Uncertainties analysis of plug-in all-electric, wireless all-electric, conventional diesel and diesel hybrid bus systems (Monte Carlo simulation results with 20,000 trials). Top whisker is the maximum, higher box bound is the third quartile, the line within the box is the median, lower box bound is the first quartile, bottom whisker is the minimum

References

[1] Hawkins TR, Gausen OM, Strømman AH. Environmental impacts of hybrid and electric vehicles—a review. Int J Life Cycle Ass 2012;17(8):997-1014.

[2] MacPherson ND, Keoleian GA, Kelly JC. Fuel economy and greenhouse gas emissions labeling for plug-in hybrid vehicles from a life cycle perspective. J Ind Ecology 2012;16(5):761-73.

[3] Davis SC, Diegel SW, Boundy RG. Transportation energy data book: Edition 33. Oak Ridge, Tennessee: Oak Ridge National Laboratory; 2014.

[4] Choi SY, Gu BW, Jeong SY, Rim CT. Advances in wireless power transfer systems for roadway-powered electric vehicles. IEEE J Emerg Sel Topics Power Electron 2015;3(1):18-36.

[5] Nguyen TD, Li S, Li W, Mi CC. Feasibility study on bipolar pads for efficient wireless power chargers. In: 2014 twenty-ninth annual IEEE applied power electronics conference and exposition (APEC), 16-20 March. IEEE; 2014. p. 1676-82.

[6] Wu HH, Gilchrist A, Sealy KD, Bronson D. A high efficiency 5 kW inductive charger for EVs using dual side control. IEEE Trans Ind Informat 2012;8(3):585-95.

[7] Ning P, Miller JM, Onar OC, White CP. A compact wireless charging system for electric vehicles. In: 2013 IEEE energy conversion congress and exposition (ECCE), 15-19 September. IEEE; 2013. p. 3629-34.

[8] Lee WY, Huh J, Choi SY, Thai XV, Kim JH, Al-Ammar EA, et al. Finite-width magnetic mirror models of mono and dual coils for wireless electric vehicles. IEEE Trans Power Electron 2013;28(3):1413-28.

[9] Tang L, Chinthavali M, Onar OC, Campbell S, Miller JM. SiC MOSFET based single phase active boost rectifier with power factor correction for wireless power transfer applications. In: 2014 twenty-ninth annual IEEE applied power electronics conference and exposition (APEC). IEEE; 2014. p. 1669-75.

[10] Budhia M, Boys JT, Covic GA, Huang CY. Development of a single-sided flux magnetic coupler for electric vehicle IPT charging systems. IEEE Trans Ind Electron 2013;60(1):318-28.

[11] Kendall A, Keoleian G, Helfand. G. Integrated life-cycle assessment and life-cycle cost analysis model for concrete bridge deck applications. J Infrastruct Syst 2008;14(3):214-22.

[12] Clark NN, Zhen F, Wayne WS, Lyons DW. Transit bus life cycle cost and year 2007 emissions estimation. Washington, DC, USA: Federal Transit Administration; 2007.

[13] AAATA. Issue analysis: Hybrid and low emission conventional bus technologies. Ann Arbor, Michigan: Ann Arbor Area Transportation Authority; 2014.

[14] Norris GA. Integrating life cycle cost analysis and LCA. Int J Life Cycle Ass 2001;6(2):118-20.

[15] Bi Z, Song L, De Kleine R, Mi C, Keoleian GA. Plug-in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. Appl Energ 2015;146:11–9.

[16] AAATA. Route schedules and maps (winter 2014, effective January 26, 2014 - May 3, 2014). Ann Arbor, Michigan: AAATA; 2014.

[17] Mi CC at Department of Electrical and Computer Engineering, University of Michigan-Dearborn, Personal communication; November, 2014.

[18] BYD Auto Company. 2013 BYD 40-ft electric bus specs, http://www.byd.com/la/auto/ebus.html; 2013 [accessed May 2014].

[19] U.S. Department of Transportation. 2013 status of the nation's highways, bridges, and transit: Conditions & performance. U.S. Department of Transportation Federal Highway Administration & Federal Transit Administration; 2013.

[20] Cooney G, Hawkins TR, Marriott J. Life cycle assessment of diesel and electric public transportation buses. J Ind Ecology 2013;17(5):689-99.

[21] Suh IS, Kim J. Electric vehicle on-road dynamic charging system with wireless power transfer technology. In: 2013 IEEE international electric machines & drives conference (IEMDC), 12-15 May. IEEE; 2013. p. 234-40.

[22] Wu HH, Gilchrist A, Sealy K, Israelsen P, Muhs J. A review on inductive charging for electric vehicles. In: 2011 IEEE international electric machines & drives conference (IEMDC), 15-18 May. IEEE; 2011. p. 143-7.

[23] Onar OC, Miller JM, Campbell SL, Coomer C, White C, Seiber LE. Oak Ridge National Laboratory wireless power transfer development for sustainable campus initiative. In: 2013 IEEE transportation electrification conference and expo (ITEC), 16-19 June. IEEE; 2013. p. 1-8.

[24] Majeau-Bettez G, Hawkins TR, Strømman AH. Life cycle environmental assessment of lithium-ion and nickel metal hydride batteries for plug-in hybrid and battery electric vehicles. Environ Sci Technol 2011;45(10):4548-54.

[25] Zackrisson M, Avellán L, Orlenius J. Life cycle assessment of lithium-ion batteries for plug-in hybrid electric vehicles–critical issues. Journal of Cleaner Production 2010;18(15):1519-29.

[26] Marano V, Onori S, Guezennec Y, Rizzoni G, Madella N. Lithium-ion batteries life estimation for plug-in hybrid electric vehicles. In: IEEE Vehicle Power and Propulsion Conference, 7-10 September. IEEE; 2009. p. 536-43.

[27] Xu B. Degradation-limiting optimization of battery energy storage systems operation [Master's]. Zurich, Switzerland: ETH Zurich; 2013.

[28] Dunn JB, Gaines L, Sullivan J, Wang MQ. Impact of recycling on cradle-to-gate energy consumption and greenhouse gas emissions of automotive lithium-ion batteries. Environ Sci Technol 2012;46(22):12704-10.

[29] U.S. EPA. eGRID: Ninth edition with year 2010 data (version 1.0). Washington, DC: U.S. EPA; 2014.

[30] Sakti A, Michalek JJ, Fuchs ERH, Whitacre JF. A techno-economic analysis and optimization of Li-ion batteries for light-duty passenger vehicle electrification. J Power Sources 2015;273:966-80.

[31] Fabbri G, Mascioli FMF, Pasquali M, Mura F, Dell'Era A. Automotive application of lithium-ion batteries: A new generation of electrode materials. In: 2013 IEEE International Symposium on Industrial Electronics (ISIE). 2013. p. 1-6.

[32] Hensley R, Newman J, Rogers M, Shahinian M. Battery technology charges ahead. McKinsey & Company; 2012.

[33] U.S. EIA. Electric power monthly with data for July 2014. Washington, DC: U.S. EIA; 2014.

[34] U.S. OMB. Discount rates for cost-effectiveness, lease purchase, and related analyses. Washington, DC: U.S. OMB; 2013.

[35] Dinger A, Martin R, Mosquet X, Rabl M, Rizoulis D, Russo M, et al. Batteries for electric cars: Challenges, opportunities, and the outlook to 2020. Boston, Massachusetts: The Boston Consulting Group; 2014.

[36] Grosjean C, Miranda PH, Perrin M, Poggi P. Assessment of world lithium resources and consequences of their geographic distribution on the expected development of the electric vehicle industry. Renewable and Sustainable Energy Reviews 2012;16(3):1735-44.

[37] U.S. EIA. Short-term energy and winter fuels outlook (STEO). Washington, DC: U.S. EIA; 2014.

[38] U.S. EIA. Annual energy outlook 2014. Washington, DC: U.S. EIA; 2014.

[39] Reikes J at BYD Motors Inc., Personal communication; July 21, 2014.

[40] Ye M, Bai Z, Cao B. Robust control for regenerative braking of battery electric vehicle. IET Control Theory & Applications 2008;2(12):1105-14.

[41] Guena T, Leblanc P. How depth of discharge affects the cycle life of lithium-metal-polymer batteries. In: 28th Annual International Telecommunications Energy Conference, 2006 INTELEC'06. IEEE; 2006. p. 1-8.

[42] U.S. EPA. The social cost of carbon. Washington, DC: U.S. EPA; 2013.

[43] Chan CC. The state of the art of electric, hybrid, and fuel cell vehicles. Proc IEEE 2007;95(4):704-18.

[44] Middleton MR. Monte carlo simulation using RiskSim. San Francisco, CA: School of Business and Management, University of San Francisco; 2001.

[45] Jang YJ, Suh ES, Kim JW. System architecture and mathematical models of electric transit bus system utilizing wireless power transfer technology. IEEE Syst J 2015;PP(99):1-12.

[46] Jeong S, Jang YJ, Kum D. Economic analysis of the dynamic charging electric vehicle. IEEE Trans Power Electron 2015;30(11):6368-77.

[47] Thornton J. Pulling power from the road: Charged by the route it follows, an electric bus gets a real world test. Mechanical Engineering: ASME; 2014. p. 44-9.

[48] Batterman J, Homa B, Hori S, Jongsma K, Li M, Mani G, et al. Let's roll: reimagining transit on Washtenaw Avenue. Michigan, United States: Taubman College of Architecture & Urban Planning, University of Michigan; 2012.

CHAPTER 4

Wireless charger deployment for an electric bus network: A multi-objective life cycle optimization

Abstract

Deploying large-scale wireless charging infrastructure at bus stops to charge electric transit buses when loading and unloading passengers requires significant capital investment and brings environmental and energy burdens due to charger production and deployment. Optimal siting of wireless charging bus stops is key to reducing these burdens and enhancing the sustainability performance of a wireless charging bus fleet. This chapter presents a novel multi-objective optimization model framework based on life cycle assessment (LCA) for siting wireless chargers in a multi-route electric bus system. Compared to previous studies, this multi-objective optimization framework evaluates not only the minimization of system-level costs, but also newly incorporates the objectives of minimizing life cycle greenhouse gas (GHG) emissions and energy consumption during the entire lifetime of a wireless charging bus system. The LCA-based optimization framework is more comprehensive than previous studies in that it encompasses not only the burdens associated with wireless charging infrastructure deployment, but also the benefits of electric bus battery downsizing and use-phase vehicle energy consumption reduction due to vehicle lightweighting, which are directly related to charger siting. The impact of charger siting at bus stops with different route utility and bus dwell time on battery life is also considered. To demonstrate the model application, the route information of the University of Michigan bus routes is used as a case study. Results from the baseline scenario show that the optimal siting strategies can help reduce life cycle costs, GHG, and energy by up to 13%, 8%, and 8%, respectively, compared to extreme cases of “no charger at any bus stop” and “chargers at every stop”. Further sensitivity analyses indicate that the optimization results are sensitive to the initial battery unit

price ($/kWh), charging power rate (kW), charging infrastructure costs, and battery life estimation methods.

4.1 Introduction

The large-scale penetration of electric vehicles (EVs) is an important strategy to mitigate the greenhouse gas (GHG) emissions, environmental impacts as well as energy consumption [1] of the transportation sector that is responsible for 27% of U.S. GHG emissions [2] and 28% of total U.S. energy use [3]. However, there are critical challenges that slow down the penetration and limit the potential for sustainability performance of EVs, stemming from: (1) the lack of accessibility and convenience of charging stations limiting the range of EVs that leads to range anxiety; and (2) the high upfront cost of EVs limiting the economic performance mainly because of the expensive and large onboard rechargeable battery [4]. Wireless power transfer (WPT) for EVs, more commonly known as the wireless charging technology [4], is an emerging charging method alternative to plug-in charging for EVs and can eliminate the two aforementioned bottlenecks of EVs. The electric energy is transferred wirelessly through an air gap from the transmitter coils embedded on the ground to the receiver coils installed on the bottom of vehicles via an electromagnetic field. Deploying wireless charging infrastructure at bus stops, traffic intersections, congestion areas as well as highways enables convenient and widespread charging accessibility [5] without the need to plug in for charging, and also enables significant downsizing (1/3–1/5 of original weight) of the heavy and expensive onboard EV battery because of multiple "opportunity charges" en route while the vehicle still fulfills the range requirements [6]. Battery downsizing has significant implications for lightweighting the vehicle and improving fuel economy [6] so as to reduce the cost of purchasing and driving an EV. Based on the charging mode, wireless charging can be classified as stationary charging, i.e., charging while the vehicle is not moving, and dynamic charging, i.e., charging when the vehicle is moving on the roadway. Transit buses, for example, can be wirelessly charged when picking up or dropping off passengers at bus stops in stationary status. Currently, there are several wireless charging electric bus routes under test in different countries and the grid-to-battery energy transfer efficiency is typically higher than 80% [4], which shows electric buses as a promising application of wireless charging technology.

Although WPT has the potential to enhance the sustainability performance of EVs by downsizing the battery and lightweighting the vehicle, the large-scale deployment of wireless charging infrastructure poses critical sustainability trade-offs in terms of economic, environmental, and energy burdens. Therefore, a comprehensive assessment framework is needed to evaluate the sustainability performance of WPT EV systems. Life cycle assessment (LCA) and life cycle cost analysis (LCCA) have been widely used to evaluate the environmental impacts, energy use, and economic performance of a product or system, which encompasses not only the use-phase burdens, but also the upfront production and manufacturing stages and end-of-life burdens. Authors of this study have previously applied LCA and LCCA to compare the life cycle energy consumption, GHG emissions, and costs of a wireless charging electric bus system with a plug-in charging electric bus system, using the bus routes in Ann Arbor, Michigan in the U.S. as a case study [6, 7]. A wireless charging electric bus system was found to have comparable life cycle burdens (costs, GHG, and energy) as an electric bus system using plug-in charging, because the additional burdens from the larger-scale wireless charging infrastructure compared to plug-in charging can be canceled out by the benefits of smaller batteries and vehicle lightweighting. Note that this conclusion is obtained when the deployment of wireless charging infrastructure at existing bus stations is not yet optimized, so this conclusion may be conservative and may underestimate the benefits of wireless charging. An optimal (or near-optimal) deployment and allocation of wireless charging infrastructure at existing bus stops would be expected to further reduce the life cycle burdens of a wireless charging electric bus system and enhance its sustainability performance.

Therefore, this study aims to investigate the reductions of life cycle burdens (costs, GHG, and energy) when optimally siting wireless charging infrastructure at existing bus stops and compare these with extreme cases of "no charger at any bus stop" and "chargers at every stop", by using a multi-objective (costs, GHG, and energy) life cycle optimization (LCO) framework. This optimization problem is a subset of facility location optimization problems. Optimization is a common tool used by researchers to explore the siting of public charging infrastructure for electric vehicles [8, 9]. Several researchers have optimized the siting of wireless charging stations for a single electric bus route [10, 11], but they lacked a comprehensive life cycle scope and only evaluated the economics of a single bus route, not incorporating other sustainability metrics, such as emissions and energy consumption and not considering the utility of a charging station and route overlapping if used in a network of routes. Systematic assessment and optimization utilizing a life cycle framework is required to effectively evaluate and understand the trade-offs between the economic, environmental, and energy burdens of large-scale WPT infrastructure deployment and the benefits of battery downsizing and fuel economy improvement.

To the best of the authors' knowledge, this is the first study to optimize the deployment of wireless charging infrastructure for a network of bus routes based on a multi-objective life cycle framework. The novel contribution of this work compared to previous studies is threefold:

- This multi-objective optimization framework evaluates not only the minimization of system-level costs, but also newly incorporates and minimizes the two key sustainability indicators of life cycle GHG emissions and energy consumption that are often evaluated in sustainability analysis of emerging technologies [6, 12].
- The LCA-based optimization framework is more comprehensive than previous studies in that it encompasses not only the burdens associated with wireless charging infrastructure deployment, but also the benefits of electric bus battery downsizing and use-phase vehicle energy consumption reduction due to vehicle lightweighting, which are directly related to charger siting.
- The multi-route setting enables evaluation of the impact of charger siting at bus stops with different route utility and bus dwell time on battery life. To exhibit the application of this model framework, the route information of the University of Michigan transit bus system (also known as the Blue Buses) is used as a case study.

This multi-objective LCO model is developed to inform research, development, and deployment of wireless charging technologies. The model formulas in the method section and the different scenario analyses in the discussion section will inform the adaptation of this model framework to other real-world scenarios in different cities with different characteristics of bus system size and vehicle miles traveled.

The rest of chapter is organized as follows. Section 4.2 describes methods of constructing the optimization model framework. Section 4.3 presents first the optimization results when solving for each objective individually, then the multi-objective results. Section 4.4 discusses the results based on several sensitivity, uncertainty, and scenario analyses. Finally key conclusions and takeaways are summarized in Section 4.5.

4.2 Methods

4.2.1 Overview of the optimization model

A multi-objective optimization model based on life cycle metrics is established to inform decision makers to strategically deploy wireless charging infrastructure at bus stations, based on the existing route network of the Blue Bus system at the University of Michigan as an example of model application. The model aims to solve for the minimal life cycle impacts in terms of costs, GHG emissions, and energy use, by selecting the best bus stations from 83 candidate stops shared by seven different bus routes with a total of 29 buses. The dwell time data from a four-day operation (2015-09-29 to 2015-10-02) were collected and provided by the University of Michigan Parking and Transportation Services, and the average dwell time of each route at each stop is used for this model. To better simulate and evaluate the application of wireless charging in bus systems, the buses in this system are all assumed to be pure electric vehicles instead of the hybrid electric or pure diesel buses currently operating in the system. These all-electric buses are assumed to be charged during picking up or dropping off passengers at the bus stops equipped with wireless chargers when their speed is zero, i.e., stationary charging. The bus schedules and dwell time at stops are assumed to remain unchanged regardless of the wireless charging availability.

As shown in Figure 4.1, a life cycle framework is established for transit agencies to compute the economic, environmental, and energy burdens of WPT infrastructure deployment and operation of a transit system of electric buses in a 24 year scope that is assumed to be equivalent of charging infrastructure life and twice the standard twelve-year life of a transit bus [7, 13, 14]. The burdens from wireless charging infrastructure, battery production and replacement, and use phase electricity consumption are aggregated to compute life cycle costs, GHG emissions, and energy use. There are 83 binary decision variables with values of either 1 or 0, indicating respectively either “deploy” or “not deploy” wireless charging infrastructure at each of the 83 candidate stops. The decision space has a total of 283 possible combinations of solutions, which is too large to conduct a complete search on all combinations of the decision variables. Therefore, genetic algorithm (GA) [15], an adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetics, is employed. Once the charger deployment is fixed in each optimization iteration, the daily state of charge (SOC) patterns of each route are obtained. Then the batteries for each route are right-sized to accommodate the SOC patterns so that the peak SOC never exceeds 95% and valley SOC never drops below 15%, which leaves room for extra travel demand and future capacity fade due to aging. The initial SOC at the start of daily operation is assumed to be 90%. Based on the SOC pattern, the battery life of each bus route is estimated using the rainflow algorithm [11, 16] (description will be provided in a later section). With the right-sized battery (kWh) and estimated battery life (years), the burdens of battery production and replacements in the 24-year scope can be quantified. The electricity consumption during bus operation is calculated by adding up the small amounts of charges at charging stations; and the electricity consumption during night hours when parked at the bus depot is computed from the difference between the end-of-day SOC and the next-day initial SOC of 90%. Therefore, the burdens from electricity use can be quantified. Finally, by summing up the burdens from infrastructure, batteries, and electricity, the total life cycle burdens are obtained. The end-of-life stage and the burdens from production and purchase of the bus itself (without battery) are constant and therefore excluded in the optimization model. The time value of money, i.e., the inflation and discount of costs of battery and electricity [7], is also considered when calculating life cycle costs.

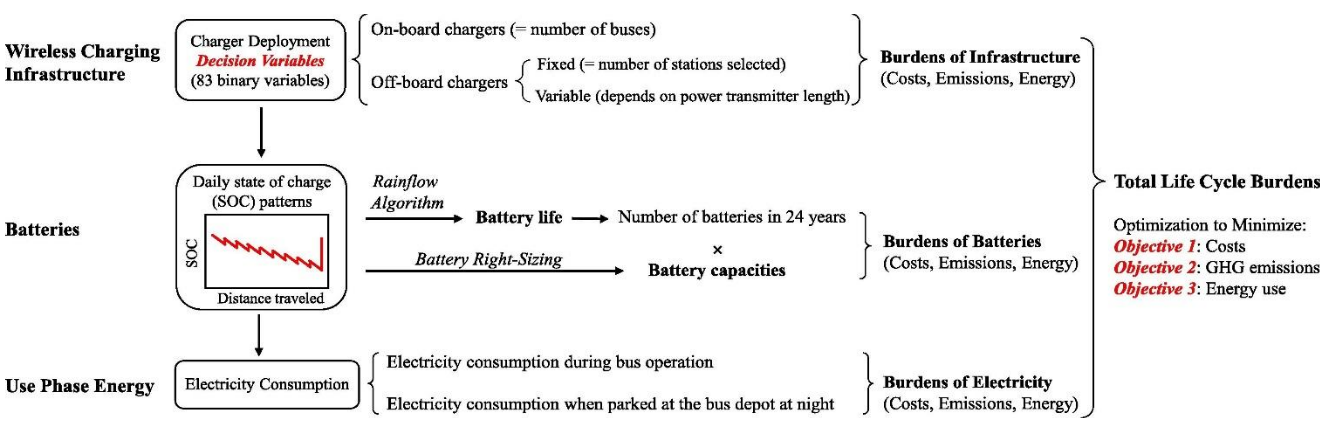


Figure 4.1 Overview of the multi-objective life cycle optimization model. GHG = greenhouse gas

4.2.2 Details of the optimization model

4.2.2.1 System equations

Eq. 4.1 − Eq. 4.8 specify the objective function, constraints, and key derivations of the optimization model, and Table 4.1 details the definitions of each variable or parameter. The model features the following characteristics, which will be detailed in the following sections: (1) Charger deployment in a nested bus route network; (2) Battery life and degradation; and (3) Temporal variation of the electric grid. Detailed descriptions of equations are provided in later sections.

Table 4.1 Definitions of variables and parameters

Symbol	***Definition***	***References***
F	Objective function, which can be life cycle costs (U.S. $), greenhouse gas emissions (kg CO_2-eq), or energy consumption (MJ)	/
α_1	Coefficient of burden for the fixed portion of 100 kW off-board wireless charging infrastructure, can be $15,000/unit, 6,040 kg CO_2-eq/unit, or 101,600 MJ/unit	[6, 7, 10]
α_2	Coefficient of burden for the variable portion of 100 kW off-board wireless charging infrastructure, can be $1,200/unit, 1,510 kg CO_2-eq/unit, or 25,400 MJ/unit	[6, 7, 10]
α_3	Coefficient of burden for the 100 kW onboard wireless charger, can be $5,000/unit, 1,717 kg CO_2-eq/unit, or 29,500 MJ/unit	[6, 7, 10]
$\alpha_{4,t}$	Coefficient of burden for the battery unit burden at year *t*, which can be $500/kWh (initially), 39 kg CO_2-eq/kWh (same for each year), or 577 MJ/kWh (same for each year)	[6, 7]
α_5	Average coefficient of burden for electricity use during bus operation, which can be $0.15/kWh, 0.7576 kg CO_2/kWh, or 9.71 MJ/kWh	[17-19]
α_6	Average coefficient of burden for electricity use when parked at depot at night, which can be $0.08/kWh, 0.7636 kg CO_2/kWh, or 9.81 MJ/kWh	[17-19]
t	A particular year, $t = 0,1,2,\ldots,24$	/
τ	Dwell time at a particular stop (minutes), $\tau \geq 0$	/
i	The stop ID number, where $i = 1,2,\ldots,83$	/
$\boldsymbol{s}$	Vector of decision variables, $\boldsymbol{s}(i) \in \{0,1\}$ where 0 = not deploy wireless chargers at stop *i*; 1 = deploy	/
$\boldsymbol{v}$	Vector of number of power transmitters (i.e., the variable part of off-board charging infrastructure) at each stop, $\boldsymbol{v}(i) \in \{0,1,2\}$	/
r	The ID number of bus route, $r = 1,2,\ldots,7$	/
n_{onWC}	Number of onboard wireless chargers, which is equal to the number of buses, $n_{\text{onWC}} = 29$	/
num_{bs}	Number of bus stops (83)	/
num_{rts}	Number of bus routes (7)	/
BatCap	Vector of battery capacity for each route (kWh)	/
BatRep	Matrix of battery replacement for each route *r* at each year *t*, $\boldsymbol{BatRep}(r,t) \in \{0,1\}$ where 1 = replace; 0 = not replace	/
$E_{\text{operation}}$	The total electricity charged during bus operation (measured at grid, kWh)	/
E_{depot}	The total electricity charged when parked at depot at night (measured at grid, kWh)	/
$\boldsymbol{T}$	Matrix of dwell time (minutes) at each stop *i* for each route *r*	/
k	The count of bus stops a particular bus encounters during a daily operation	/

$\boldsymbol{e}_k$	Cumulative daily electricity demand (kWh) for each route *r* until stop *k* for battery sizing purpose, and $\boldsymbol{e}_0 = 0$	/
$\boldsymbol{e}$	Vector of cumulative daily electricity demand (kWh)	/
ECR_{base}	The base energy consumption rate (ECR) of an all-electric bus (2 kWh/mile ≈ 1.24 kWh/km)	[20]
$\boldsymbol{ECR'}$	The adjusted energy consumption rate (kWh/mile) for each route *r* by considering the lightweighting effects	/
$\boldsymbol{d}_k$	The distance (miles) between stop *k* and stop *k*+1 for each route *r*	/
η_{c}	The wireless charging efficiency (grid-to-battery) = 85%	[4, 6]
$\eta_{\text{b},t}$	The battery round-trip efficiency at particular year *t*, which fades over time from 90% to 72%	[21, 22]
P	The charger power rate (100 kW)	[10]
SOC_{initial}	The initial state of charge (SOC) at the start of day, $SOC_{\text{initial}} = 0.9$	/
SOC_{lb}	The minimum SOC threshold (lower bound), $SOC_{\text{lb}} = 0.15$	/
SOC_{ub}	The maximum SOC threshold (upper bound), $SOC_{\text{ub}} = 0.95$	/
$\boldsymbol{SOC}_k$	State of charge (SOC) at stop *k* for each route *r*, $SOC_0 = SOC_{\text{initial}} = 0.9$	/
$BatWgt_{\text{base}}$	The base battery weight (2,492 kg) of an all-electric bus	[12, 20]
$BusWgt_{\text{base}}$	The base bus weight (15,000 kg)	[20]
ρ	Battery specific energy (0.13 kWh/kg)	[12]
$\boldsymbol{R}_{\text{adj}}$	Ridership weight (kg) adjustment for each route *r* (the deviation from base ridership)	/
σ	Lightweighting correlation (4.5% energy reduction per 10% electric bus mass reduction)	[6]

Note: 1 mile ≈ 1.609 km.

Heuristic algorithms are appropriate for solving this discrete optimization problem with a large decision space of 283 possible solutions. GA [15] in Matlab is employed to solve this optimization problem with discrete integer decision variables. Note that because GA is a heuristic algorithm, there is no guarantee that the final solution is the global optimum. Therefore, the following efforts are taken to increase the chances of converging closer to the global optimum: (1) using a strict and adaptive stop criterion, so that the algorithm runs until the average relative change in the fitness function value over consecutive generations is less than or equal to the user-defined function tolerance (1e−18) that is much stricter than the Matlab default; (2) setting the maximum number of generations/iterations at a very high value (e.g., greater than 1e5) so that a premature stop (i.e., reaching the maximum number of iterations before the algorithm converges) is prevented;

and (3) solving the problem with 100 different initial conditions based on a random uniform distribution. Thus, with these efforts, a near-optimal solution is obtained, which is deemed adequate for the purposes of this work in terms of demonstrating the utility of the developed framework. Hence, in this study, the term "optimum" or "optimal" refers to "near-global-optimum" or "near-global-optimal". The typical time needed to reach convergence is one to two hours, which is reasonable for a transit agency at the planning stage when deciding at which bus stops to deploy wireless chargers.

Objective function:

The objective function Eq. 4.1 summarizes burdens from off-board and onboard wireless chargers, batteries, and electricity use during bus operation and night. By using the corresponding coefficients for cost, GHG, or energy, this equation can calculate the life cycle costs, GHG, or energy.

$$\min F = \alpha_1 \sum_{i=1}^{num_{\text{bs}}} \boldsymbol{s}(i) + \alpha_2 \sum_{i=1}^{num_{\text{bs}}} \boldsymbol{v}(i) + \alpha_3 n_{\text{onWC}} + \sum_{t=0}^{24} \sum_{r=1}^{num_{\text{rts}}} \alpha_{4,t} \boldsymbol{BatCap}(r) \boldsymbol{BatRep}(r,t) + \alpha_5 E_{\text{operation}} + \alpha_6 E_{\text{depot}}$$

(Eq. 4.1)

Constraints or key definitions:

Eq. 4.2 defines a matrix of dwell time (minutes) at each stop i for each route r.

$$\boldsymbol{T}(i,r) = \tau \quad \text{where } i = 1, 2, \ldots, num_{\text{bs}};\ r = 1, 2, \ldots, num_{\text{rts}};\ \tau \geq 0 \qquad \text{(Eq. 4.2)}$$

Eq. 4.3 defines the binary decision variable vector, where 0 means "not deploy wireless chargers at stop i" and 1 means "deploy".

$$\boldsymbol{s}(i) \in \{0,1\} \quad \text{where } i = 1, 2, \ldots, num_{\text{bs}} \quad \text{(Decision variables)} \qquad \text{(Eq. 4.3)}$$

Eq. 4.4 defines the vector of number of power transmitters at each bus stop.

$$\boldsymbol{v}(i) = \begin{cases} 0 & \text{if } \boldsymbol{s}(i)=0 \\ 2 & \text{if stop } i \text{ is shared by at least two routes and any one dwells at least 0.5 minute} \\ 1 & \text{otherwise} \end{cases}$$

(Eq. 4.4)

Eq. 4.5 calculates the cumulative daily electricity demand (kWh) for each route r until stop k for battery sizing purpose.

$$\boldsymbol{e}_{k+1}(r)=\begin{cases}\boldsymbol{e}_k(r)+ECR_{\text{base}}\boldsymbol{d}_k(r)-\eta_c\eta_{b,t}P(\frac{\tau}{60}) & \text{if charger available}\\ \boldsymbol{e}_k(r)+ECR_{\text{base}}\boldsymbol{d}_k(r) & \text{if charger not available}\end{cases}$$
$$\text{where } \boldsymbol{e}_0=0 \qquad \text{(Eq. 4.5)}$$

Eq. 4.6 calculates battery capacity for each route in kWh.

$$\boldsymbol{BatCap}(r)=\max\{(\max(\boldsymbol{e}(r))-\boldsymbol{e}_0)/(SOC_{\text{initial}}-SOC_{\text{lb}}),\ 25\,\text{kWh}\} \qquad \text{(Eq. 4.6)}$$

Eq. 4.7 calculates the adjusted energy consumption rate (kWh/mile) for each route r by considering the lightweighting effects of battery downsizing.

$$\boldsymbol{ECR'}(r)=ECR_{\text{base}}\cdot\left[1-\frac{BatWgt_{\text{base}}-\boldsymbol{BatCap}(r)/\rho+\boldsymbol{R}_{\text{adj}}(r)}{BusWgt_{\text{base}}}\cdot\sigma\right] \qquad \text{(Eq. 4.7)}$$

Eq. 4.8 calculates the battery state of charge (SOC) at stop k for each route r.

$$\boldsymbol{SOC}_{k+1}(r)=\begin{cases}\boldsymbol{SOC}_k(r)-\dfrac{\boldsymbol{ECR'}(r)\boldsymbol{d}_k(r)}{\boldsymbol{BatCap}(r)}+\dfrac{\eta_c\eta_{b,t}P(\frac{\tau}{60})}{\boldsymbol{BatCap}(r)} & \text{if } \boldsymbol{SOC}_{k+1}(r)\le SOC_{\text{ub}}\\ SOC_{\text{ub}} & \text{otherwise}\end{cases}$$
$$\text{where } SOC_0=SOC_{\text{initial}}=0.9 \qquad \text{(Eq. 4.8)}$$

4.2.2.2 Charger deployment in a nested bus route network

The bus system under evaluation is a network of bus routes nested together, with some bus stops shared by two or more routes and some exclusively used by a single route. Different from optimizing a single route which only requires the model to consider the dwell time at each stop, optimizing a network of routes requires the model to characterize the effect of sharing a stop by multiple routes and the utility of a charging station. As shown in Eq. 4.2, an 83×7 matrix $\boldsymbol{T}$ of dwell time in minutes at each stop (83 stops) for each route (seven routes) is established. If a stop is selected for deploying charging infrastructure, its stop identification (ID) number will be matched with the stop ID in matrix $\boldsymbol{T}$ so that it would be able to calculate the charged electric energy for all the routes sharing that stop. The names of the seven routes are: (1) Bursley-Baits; (2) Commuter North & South; (3) Northwood; (4) Diag-to-Diag Express; (5) Northwood Express; (6) Oxford Shuttle; and (7) Wall Street.

The off-board wireless charger is calculated separately as a fixed part and a variable part. The fixed part is mainly composed of the inverter and grid connection. The burden from this part is fixed regardless of the length of the power transmitter (i.e., the variable part). The burden from the variable part is proportional to the length of the power transmitter. The fixed burden of charging infrastructure in the entire system is determined by the total number of charging stations, i.e., $\sum_{i=1}^{83} \boldsymbol{s}(i)$. On the other hand, the variable length at a particular stop is determined by Eq. 4.4 based on the dwell time at the stop and number of buses sharing that stop. The variable burden of charging infrastructure in the entire system is determined by the total units of variable parts, i.e., $\sum_{i=1}^{83} \boldsymbol{v}(i)$.

4.2.2.3 Battery life and degradation

Batteries for each route are sized by Eq. 4.5 and Eq. 4.6. First, the cumulative daily battery energy demand for each route is calculated using Eq. 4.5. Battery capacity is calculated using Eq. 4.6 so that the battery has enough room to accommodate the energy demand and leaves extra capacity for future capacity fade and unexpected usage. A minimum battery capacity of 25 kWh is assumed in order to ensure bus operation even if the calculated capacity could be less than 25 kWh. The battery chemistry is assumed to be lithium-ion in this study.

After the battery capacity for each route is determined, the actual average energy consumption rate ***ECR'*** (kWh/mile) for each route is calculated using Eq. 4.7. This equation first computes the percentage of vehicle weight reduction due to battery downsizing from the base vehicle and then the change in energy consumption rate is correlated with the change in vehicle weight by the lightweighting correlation σ [6]. The energy consumption rate is also adjusted for the average ridership difference among different routes. Therefore, the lightweighting benefit of energy consumption rate reduction due to battery downsizing is modeled.

The daily SOC curve for each route can be obtained by using Eq. 4.8 after the battery capacity and actual average energy consumption rate are determined. A rule of not exceeding 95% SOC is applied so that the battery is never overcharged. The battery is also never over-drained because the batteries have been sized to accommodate the maximum energy demand and have extra capacity.

Battery degradation and life can be estimated by models based on either experimental data or analytical approaches, which characterize the effects of ambient temperature, state of charge profile, and/or depth of charge or discharge [23]. Models with different characteristics serve different research needs with considerations of estimation precision, simplicity for implementation, and computation time. In this study, the battery life is estimated using the rainflow algorithm [11, 16] for its simplicity to incorporate battery degradation into life cycle analysis by counting multiple full and half cycles of charge/discharge in the daily SOC curves. The correlation equation of theoretical cycle life (*Cycles*) and depth of discharge (*DoD*) of a lithium-ion battery is based on [24] and shown in Eq. 4.9. This is also called the fatigue model, where the working *DoD* of different full and half cycles is translated to cumulated battery fatigue as an indicator for battery retirement. For details of this battery life estimation method, please refer to [11, 16]. Among different battery chemistries (e.g., lead-acid, nickel metal hydride, and lithium-ion), lithium ion battery is one of the most common battery chemistries for EVs. If a different battery chemistry is to be used, then replace it with the corresponding regression equation describing the non-linear curve of cycle life vs. depth of discharge of that particular battery chemistry.

$$Cycles = (DoD / 145.71)^{(-1/0.6844)} \quad \text{(Eq. 4.9)}$$

As the battery ages, the round-trip efficiency is assumed to drop linearly from 90% to 72% [21, 22].

4.2.2.4 Temporal variation of the electric grid

To more precisely estimate the use phase electricity costs, emissions, and energy consumption of electricity use, the optimization model also considers the temporal variations of the electricity price ($/kWh) and emissions (kg CO_2/kWh), and energy consumption (MJ/kWh) intensities of electricity generation. The variations are mainly due to the dispatch of different power plants to meet the varying demand during a day. The annual average temporal variations of CO_2 and energy intensities of the electricity generation of the Great Lakes/Mid-Atlantic region are calculated and shown in Figure 4.2 using the AVoided Emissions and geneRation Tool (AVERT model) by the U.S. Environmental Protection Agency (EPA) [19]. There are distinct differences in the CO_2 and energy intensities between the bus operation hours (i.e., 6 AM–10 PM) and overnight hours parked at depot (i.e., 11 PM–6 AM). Therefore, the temporal variations are generalized into two categories: operation and depot hours, and average intensities are assumed for each category, as indicated by α_5 and α_6 in Eq. 4.1. The electricity prices for each category are based on the U.S. Energy Information Administration (EIA) electricity price of the transportation sector in Michigan and calculated using the ratio of on-peak and off-peak electricity prices offered by the DTE Energy [17, 18]. The specific values of the intensity coefficients of α_5 and α_6 are provided in Table 4.1.

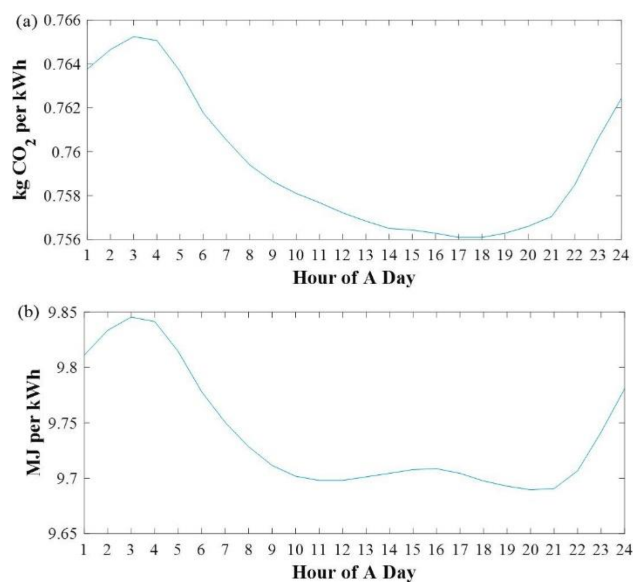


Figure 4.2 Annual average temporal variations of carbon dioxide and energy intensities of the electric grid of the Great Lakes/Mid-Atlantic region in the AVoided Emissions and geneRation Tool (AVERT model) [19]

4.3 Results

4.3.1 Single-objective optimization results

The optimization model is first solved for each objective separately. The respective values of objective function, total stops selected, battery capacity, and battery life at optima are summarized in Table 4.2 for each single objective of life cycle costs, GHG emissions, or energy consumption. The breakdown of life cycle burdens for each objective is illustrated in Figure 4.3. The selected bus stops at the optimal life cycle costs as an example are mapped in Figure 4.4. The SOC curves for each route at life cycle cost optima can be found in the Appendix.

Table 4.2 Single-objective optimization results

		Cost	GHG	Energy
Objective function ($, kg CO_2-eq, or MJ)		9,644,967	45,182,578	582,657,784
Number of stops selected out of 83 stops		42	55	52
Battery capacity (kWh)	Route 1	68	68	68
	Route 2	84	74	76
	Route 3	105	100	100
	Route 4	57	48	48
	Route 5	85	56	67
	Route 6	25	25	25
	Route 7	79	65	65
Battery life (years)	Route 1	6.6	6.6	6.6
	Route 2	6.5	6.5	6.5
	Route 3	6.6	6.6	6.5
	Route 4	7.3	6.9	6.9
	Route 5	7.8	6.8	7.3
	Route 6	8.6	9.9	9.9
	Route 7	6.8	6.8	6.8

Note: GHG = greenhouse gases.

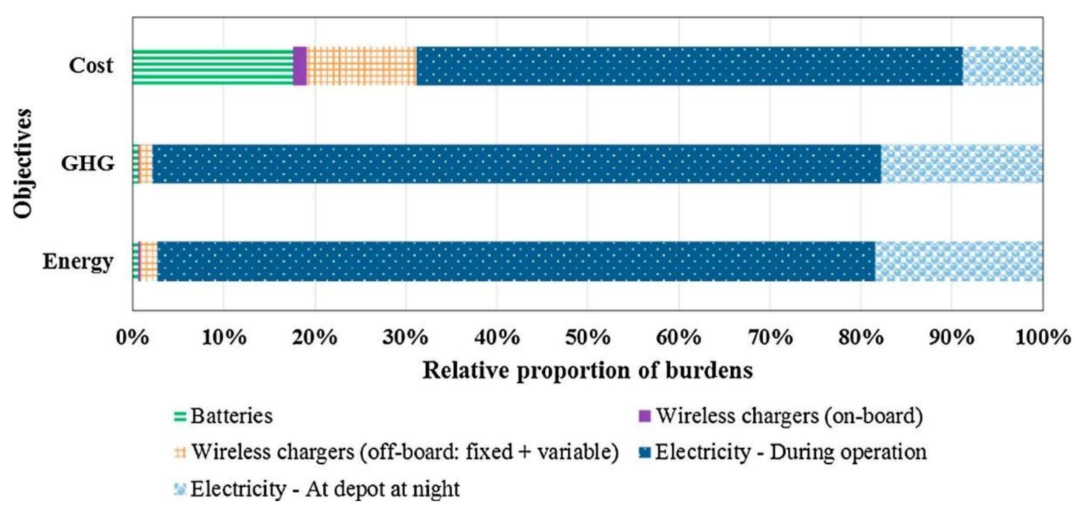
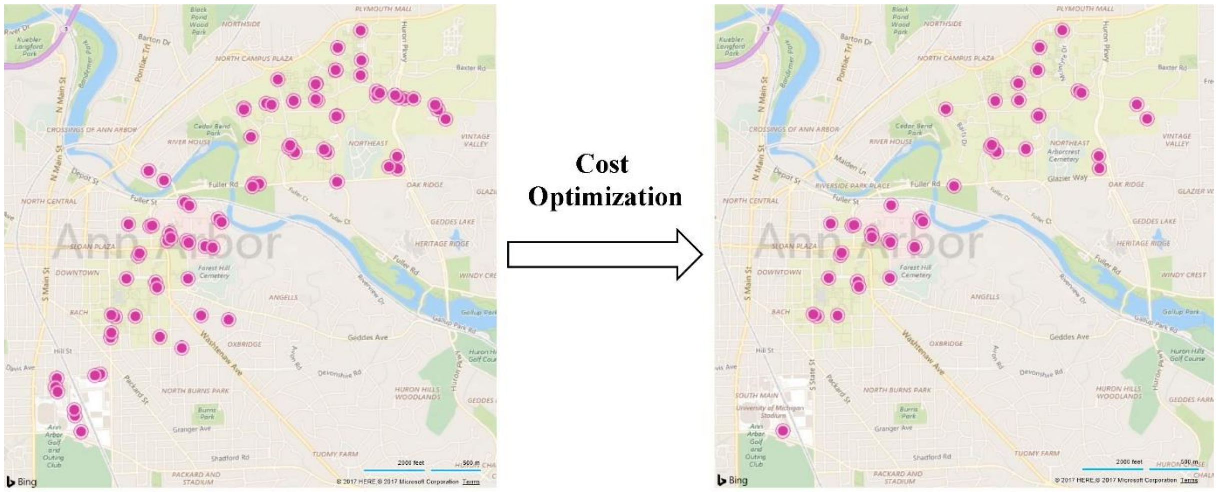


Figure 4.3 Breakdown of optimal life cycle burdens for the single objective of life cycle costs, greenhouse gas (GHG) emissions, and energy consumption



Original: 83 stops **Selected: 42 stops**

Figure 4.4 Optimal stations to deploy wireless charging infrastructure at the minimal life cycle costs

4.3.2 Multi-objective optimization results

Multi-objective optimizations are conducted for the paired objectives of (1) life cycle costs and GHG emissions and (2) life cycle costs and energy. Note that life cycle GHG and energy objectives are not paired and the three objectives are not solved together because GHG and energy objectives are similar according to Figure 4.3. The corresponding objective values at different numbers of selected stops, trade-off zones of the two objectives, and the respective Pareto frontiers (i.e., alternative illustrations of the trade-off zones) are shown in Figure 4.5. The trade-off zone is defined as the range of number of selected stops between the optimum of one objective and the optimum of the other objective. For example, the cost and GHG objectives reveal the same monotonic patterns when the number of selected stops is below 42 and over 55. However, the cost objective trades off with the GHG objective when the number of selected stops is between 42 and 55. The Pareto frontier also illustrates such a trade-off and is obtained by weighting the two objectives that are normalized against their own optimal objective function values. Similarly, the cost and energy objectives have a trade-off zone between 42 and 52 stops. The majority of the stops selected for these objectives are the same, i.e., most of these selected stops are always selected regardless of which objective. At the optimal life cycle costs, the life cycle burdens of GHG and energy are close to their respective optima. The changes in the values of life cycle objectives in these trade-off zones are smaller than 1%. These weak trade-offs among these objectives indicate that when siting the chargers for the minimal life cycle costs, planners would also achieve the approximate life cycle GHG and energy minima.

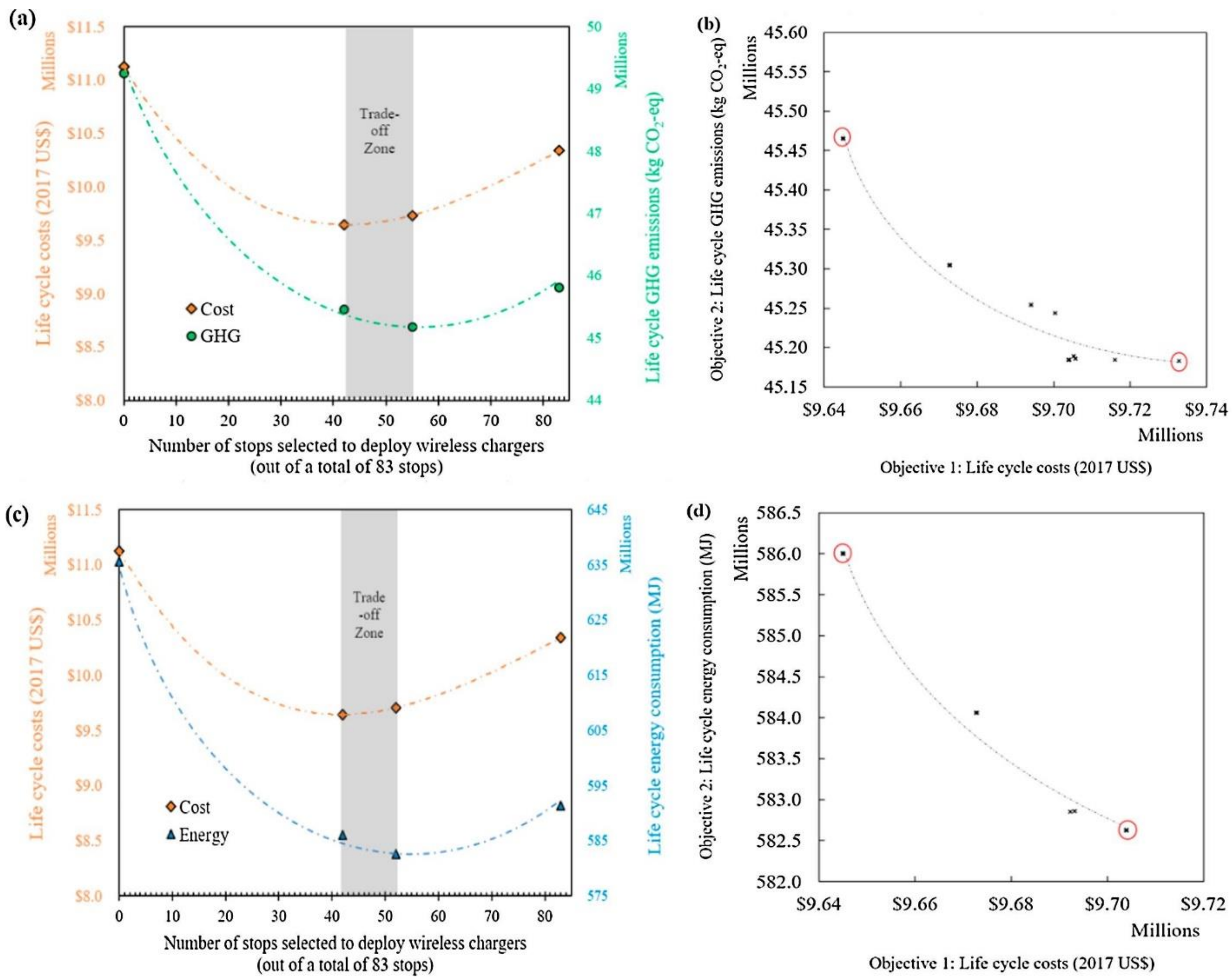


Figure 4.5 Multi-objective optimization: (a) Cost and GHG objectives; (b) Pareto frontier of cost and GHG objectives; (c) Cost and energy objectives; (d) Pareto frontier of cost and energy objectives. The trend lines for the objectives are polynomial approximations. The Pareto lines are illustrations of the frontiers. The red circles indicate the extreme values in the Pareto frontiers. GHG = greenhouse gases

Results show that the optimal siting strategies of wireless charging infrastructure at selected bus stops can help reduce life cycle costs, GHG emissions, and energy by up to 13%, 8%, and 8%, respectively, compared to non-optimal cases. Neither the case of "no wireless charging stations at all" nor the case of "wireless chargers at every bus stop" would be optimal because the battery capacity can be large and expensive when there is no wireless charging stations at all and there is a trade-off of battery life and wireless charging infrastructure burden when there are chargers at every bus stop.

The temporal variation of the electric grid plays an important role in trading off the cost objective and two other objectives. With more bus stops selected to deploy wireless charging infrastructure, a higher percentage of electricity is charged during bus operation hours when the electricity is more expensive due to peak hours but cleaner due to the dispatch of cleaner energy sources and thus a lower proportion of electricity is charged at night at the depot when the electricity is cheaper but more polluting because of the baseload coal or other pollution-intensive and energy-intensive power plants. Therefore, the optimal number of charging stations tends to be greater for the GHG and energy objectives than for the cost objective.

4.4 Discussion

4.4.1 Sensitivity analyses

The optimization results can be sensitive to the changes in initial battery unit price ($/kWh), charging power rate (kW), and charging infrastructure cost ($/unit of on-board, fixed off-board, or variable off-board portion of the wireless charger). To evaluate the sensitivity, these parameter values are varied based on their probable ranges with the objective of minimizing life cycle costs, and the corresponding values of objective functions, number of stops selected, fleet-average battery capacity, and fleet-average battery life are plotted in Figure 4.6.

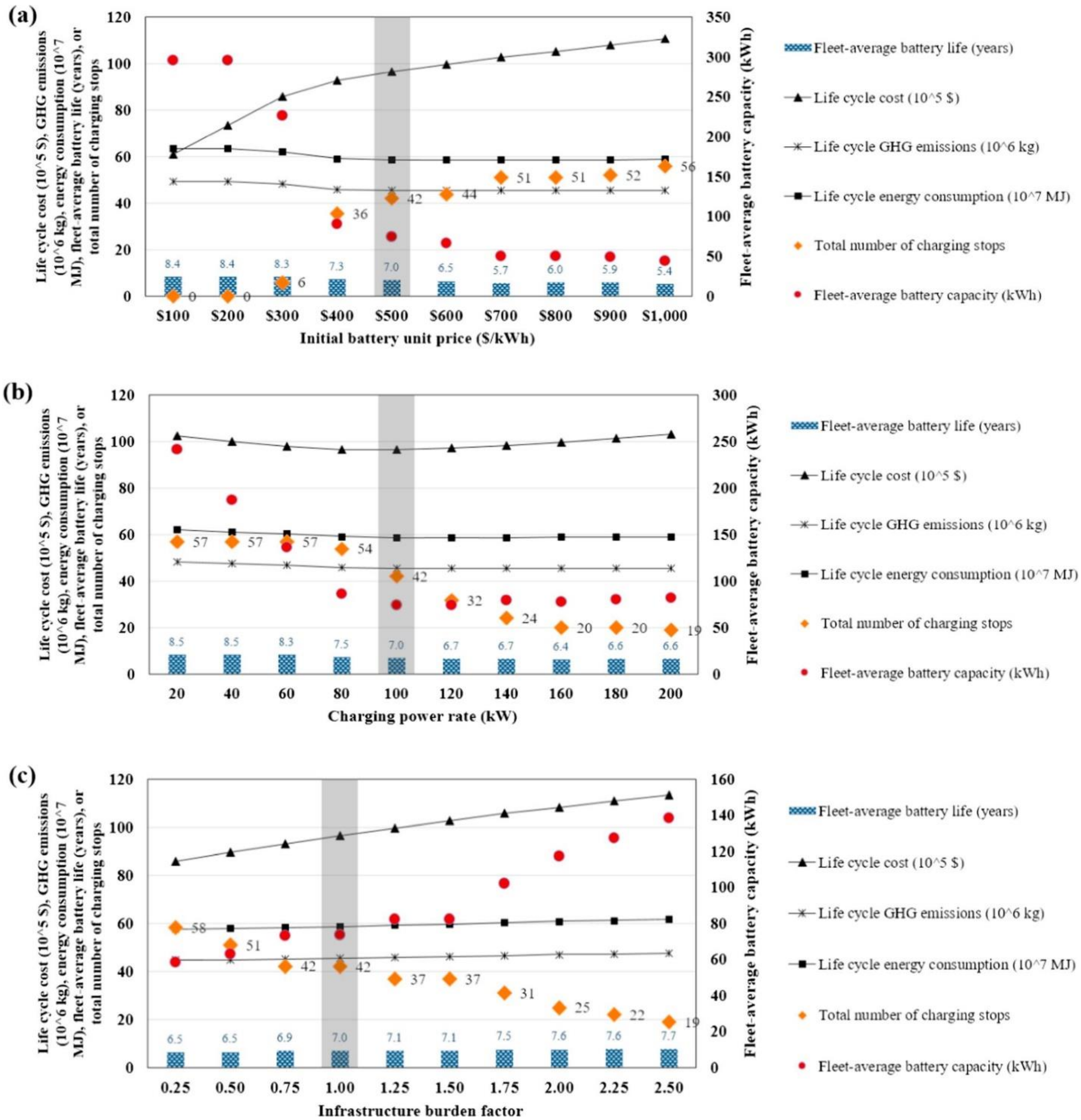


Figure 4.6 Sensitivity analyses of (a) initial battery unit price ($/kWh), (b) power rate of charging (kW), and (c) charging infrastructure costs. The base cases are highlighted by gray shaded areas. GHG = greenhouse gases

If the initial battery unit price varies from $100 to 1000/kWh, there is a tendency to size the battery smaller, which requires more charging stations so that the battery never runs out during operation with a compromise of battery life. The results are consistent with the sensitivity analysis reported in [25] which optimized the online electric vehicle (OLEV) in Korea and also showed the trade-off between the battery capacity and charging infrastructure.

If the charging power rate varies from 20 to 200 kW, it means a faster charging rate so that more electricity can be charged at charging stops for the same period of time, which allows for a smaller number of charging stations and correspondingly smaller battery capacity but shorter battery life. The objective values dip first and then slightly increase or flatten because a higher power rate also scales up the charging infrastructure burdens, which cancels out some of the benefits brought by a higher power rate.

Due to the uncertainty of charging infrastructure costs at the current stage of wireless charging implementation, a sensitivity analysis is conducted. If the infrastructure costs vary from 0.25 to 2.5 times relative to its base assumed values, the number of charging stations selected decreases from 58 to 19 stops, the battery capacity increases, and battery life increases.

The temporal variability of the electric grid in terms of carbon and energy intensities would result in a trade-off of the cost objective with the GHG and energy objectives because of the difference in fuel profiles and energy demand between night hours and daily bus operation hours. The sensitivity of the trade-off zones with respect to the temporal variation in the carbon and energy intensities of the electric grid between night hours and daily bus operation hours is shown in Figure 4.7. If the grid is cleaner and less energy intensive during bus operation hours due to more renewable energy penetration compared to night hours, the optimal numbers of charging stations for the GHG and energy objectives tend to increase so that more electricity can be charged when the grid is clean and energy efficient instead of during nighttime when the electricity is usually composed of carbon intensive and inefficient fuel sources. Therefore, the trade-off zone increases with the increase in the ratio of grid intensities between night and day. The results indicate that when the temporal variation is large and the grid is much cleaner and more energy efficient in the daytime than the nighttime, an almost full coverage of wireless charging infrastructure would be favorable in terms of carbon emissions and energy consumption.

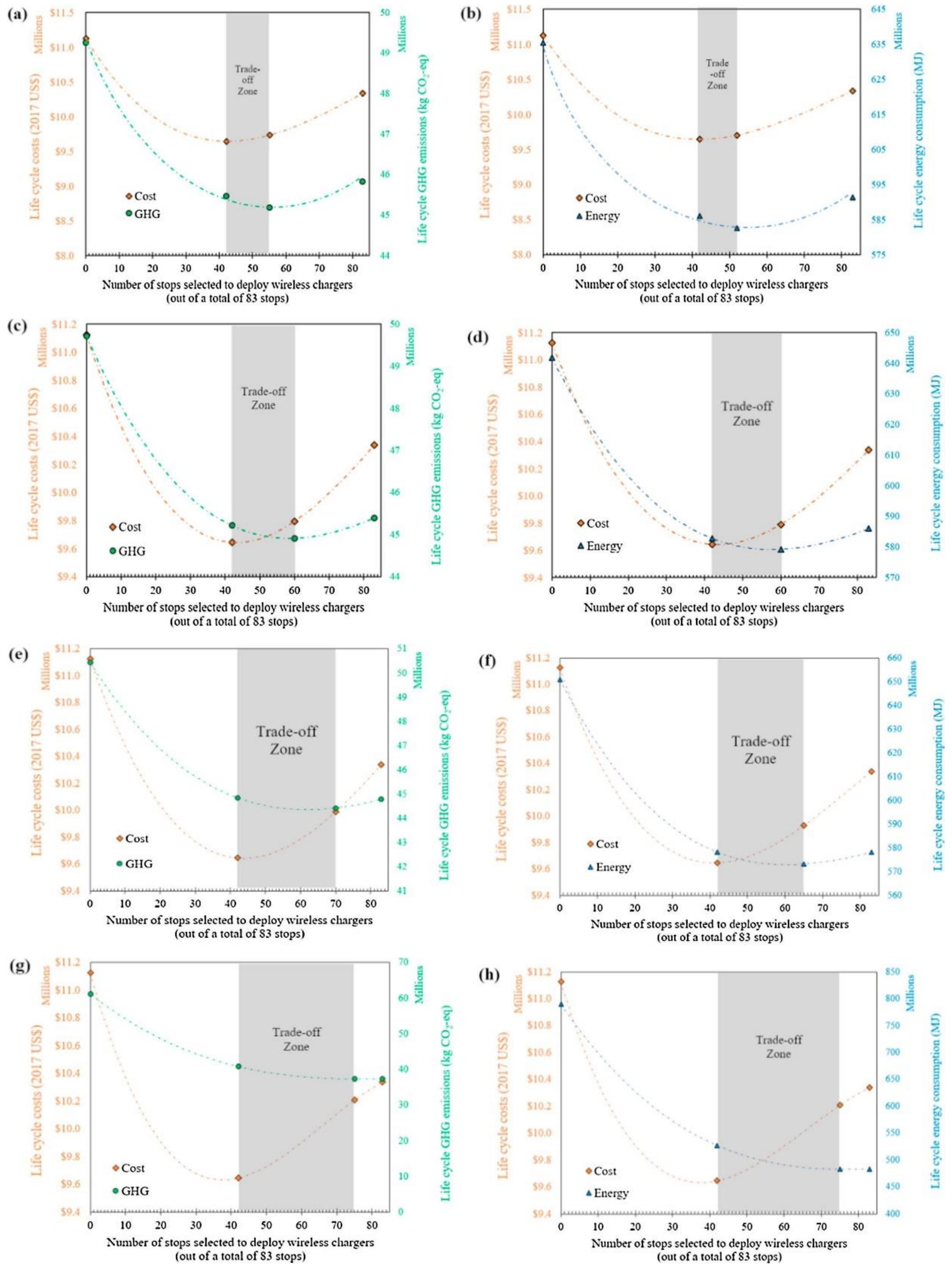


Figure 4.7 Sensitivity of the trade-off zones with respect to the temporal variation in the carbon and energy intensities of the electric grid between night hours and daily bus operation hours. The base case is shown in (a) and (b). The ratio of grid intensities between night and day is increased to 1.01 (c, d), 1.025 (e, f), and 1.25 (g, h) times than the base case. The trend lines are polynomial approximations of the scattered dots. GHG = greenhouse gases

Another sensitivity analysis is conducted on the method of battery life estimation. In the base case, the rainflow counting algorithm [11, 16] has been implemented to estimate battery life, which can well quantify the battery fatigue from the multiple small charge and discharge cycles due to wireless charging throughout the daily operation. To evaluate the effect of battery life estimation method on the optimization results, a battery energy-processed model of the $LiFePO_4$ battery chemistry based on lab experiment [26] is implemented here for a sensitivity analysis. In this method, a battery is assumed to be retired when each cell (3.63 Wh) in this battery has processed 34.3 kWh of electricity (at a threshold of 80% usable nameplate capacity left at end of life), or retired at the end of bus life, whichever comes earlier.

Results indicate that the optimal number of stops selected would be 35, 59, and 57 for the life cycle cost, GHG, and energy objectives, respectively (as a reference, the optimal number of stops selected is 42, 55, and 52 in the base case, respectively). This means the minimal life cycle costs would be achieved with fewer number of charging stops and the minimal life cycle GHG and energy are achieved with slightly more charging stops, but most of the stops selected in the base case remain selected in spite of a different battery life estimation method. As a result, the trade-off zones for the two pairs of objectives become slightly larger. Detailed results can be found in the Appendix.

4.4.2 Uncertainty analysis

A bus stop is selected to deploy wireless charging infrastructure based on the duration of each bus stopping at that stop (i.e., the dwell time) and how frequent and intensive the bus station is used and shared (i.e., the utility). Therefore, the siting of charging stations can be sensitive to the bus dwell time at each bus stop. For the base case, the four-day average dwell time data for each bus stop is used. In this uncertainty analysis, the dwell time at each stop is randomly assigned from a normal distribution with a standard deviation of 20% based on its original four-day average value.

The first part of the uncertainty analysis investigates the effect of dwell time uncertainty on the number of selected bus stops. Life cycle cost objective is used as an example. When the bus dwell time is normally distributed, the number of selected stops varies from 32 to 46 with a median of 38 stops, which is less than the 42 stops selected for the base case. This means that if some bus stops that are originally selected are assigned a shorter dwell time, these stops will not be selected, and those under-utilized stops that are originally not selected will still remain unselected even though they are assigned a longer dwell time.

The second part of the uncertainty analysis investigates the effect of dwell time uncertainty on the objective function values and battery metrics with the fixed bus station siting (42 stops are selected when the life cycle cost is minimized in the base case). The variabilities of objective function values and fleet-average battery capacity and life with respect to the randomly and normally distributed bus dwell time data are shown in Figure 4.8. The life cycle cost objective values reveal more uncertainty than the life cycle GHG and energy objectives, and the fleet-average battery capacity shows greater uncertainty than the fleet-average battery life. According to Figure 4.3, a greater proportion of burden is from the batteries for the life cycle cost objective than the GHG and energy objectives, which would explain why the life cycle cost objective values reveal a greater uncertainty.

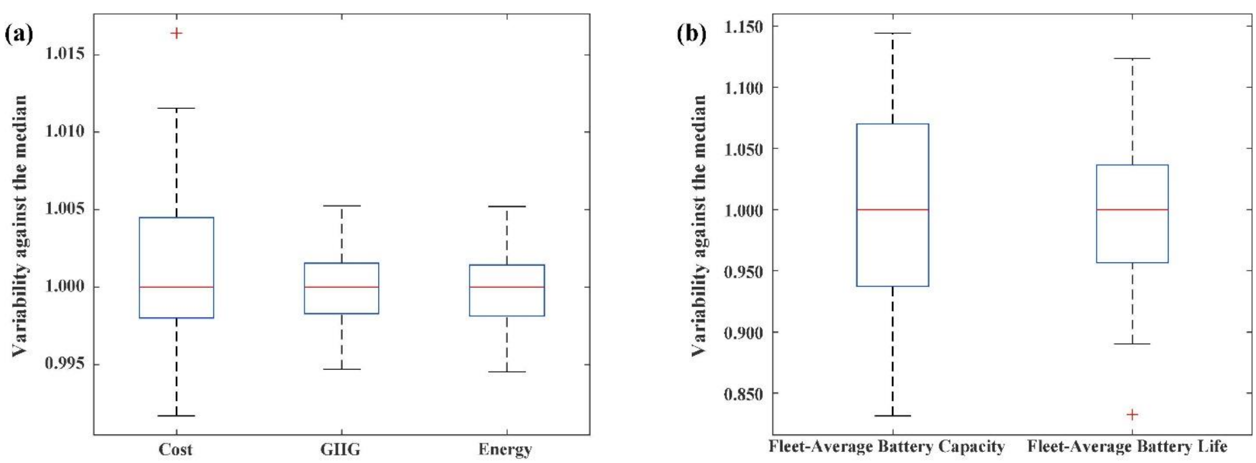


Figure 4.8 Uncertainty analysis of bus dwell time: (a) life cycle cost, greenhouse gas (GHG), and energy objectives; (b) fleet-average battery capacity and life. The output values of the uncertainty analysis are normalized against their respective median values so that the boxplots show the minimum, first quartile, median, third quartile, maximum, and outlier values of 50 iterations on the same scale

4.4.3 Scenario analysis

4.4.3.1 Social cost of carbon

The U.S. EPA established a mechanism to evaluate the carbon emissions using the social cost of carbon (*SCC*) [27]. By monetizing the carbon emissions, the two objectives of life cycle costs and GHG emissions in the optimization model can be unified into a single grand objective function, as shown in Eq. 4.10,

$$F_{\mathrm{G}} = F_{\mathrm{cost}} + F_{\mathrm{GHG}} \cdot SCC \cdot \frac{1\,\mathrm{t}}{1000\,\mathrm{kg}} \qquad \text{(Eq. 4.10)}$$

where F_{G} is the grand objective function ($), F_{cost} is the objective function of life cycle costs ($), F_{GHG} is the objective function of life cycle GHG emissions (kg), SCC is the social cost of carbon ($/metric tonne CO_2). Similar to the calculation of life cycle costs, the life cycle GHG emissions include not only the emissions of charger production, but also the use-phase emissions from electricity use.

Therefore, the external impact of carbon emissions can be internalized and expressed in the same unit of dollars when optimizing the siting of charging stations. A scenario analysis is conducted to investigate the effect of different valuations of *SCC* on the charging station selection and battery sizing, as shown in Figure 4.9. With an increase in the SCC, the optimal number of selected stops to deploy wireless charging infrastructure tends to grow and then saturates at 51 stops selected, compared to the 55 stops selected when considering GHG only as shown previously in Table 4.2. Accordingly, the fleet-average battery capacity tends to decrease because more charging stations become available. The results indicate that there would be more coverage of wireless charging infrastructure when more emphasis is put on the social cost of carbon emissions.

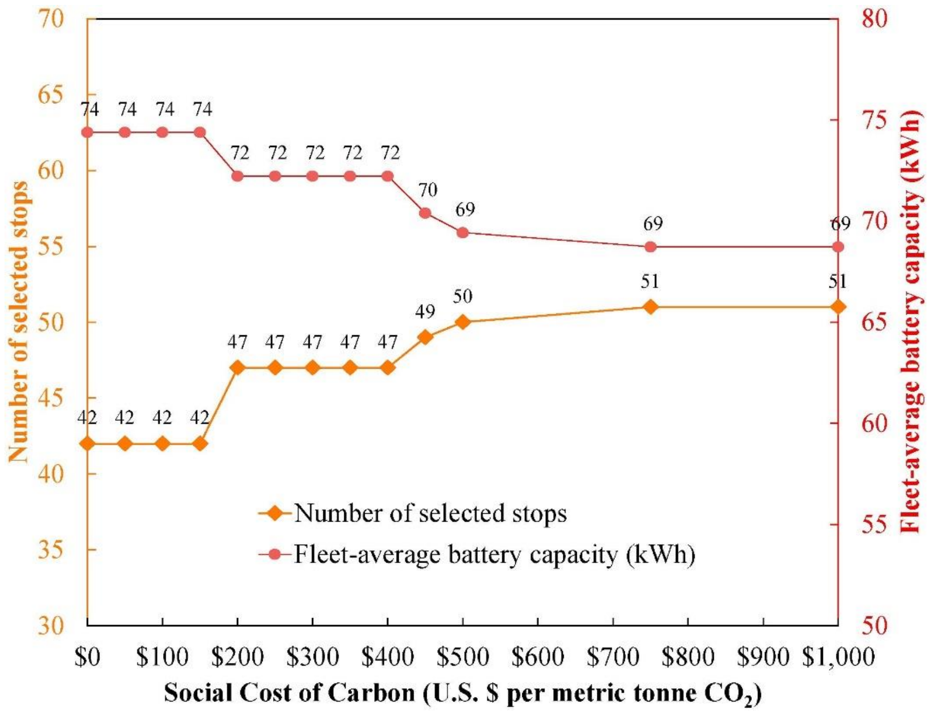


Figure 4.9 Scenario analysis of the social cost of carbon

4.4.3.2 Utility of bus stations

A large city with decentralized routes versus a compact city with routes overlapping with one another would have different optimal deployment scenarios of wireless charging infrastructure because of different levels of overlapping routes which can be characterized by the utility rate of bus stations, defined as the average number of routes per bus stop. In the base case, the utility of bus stations is 1.62 routes per stop. In this scenario analysis, the utility is increased to 1.75 routes per stop by imposing some stops in proximity to be combined into a single stop so that the bus system provides the similar service with fewer total bus stops. The optimization shows that with a higher utility of bus stations, fewer optimal charging stops are required (36, 48, and 45 stops selected compared to 42, 55, and 52 stops for the base case for the cost, GHG, and energy objectives, respectively) and a lower fraction of total burden comes from the charging infrastructure (12.8%, 1.5%, and 1.8% compared to the base case 13.6%, 1.6%, and 2.0% for the cost, GHG, and energy objectives, respectively). Therefore, the design of a more compact bus system with high utility of bus stations would help reduce the relative burdens of charging infrastructure, and a more geographically distributed bus system with low utility of bus stations would have a higher proportion of burdens from the charging infrastructure. Detailed optimization results of this scenario analysis can be found in the Appendix.

4.5 Conclusions

In this study, a multi-objective life cycle optimization model framework is established to guide research, development, and deployment of wireless charging technologies by characterizing the trade-offs of large-scale wireless charging infrastructure deployment versus the battery downsizing and vehicle lightweighting benefits, and develop strategies to inform decision makers regarding the optimal siting scenarios of wireless charging infrastructure for an electric bus system. The utility of model framework is demonstrated by a case study using the route information of the existing bus route network at the University of Michigan, Ann Arbor. Results from the baseline scenario show that the optimal siting strategies of wireless charging infrastructure at selected bus stops can help reduce life cycle costs, GHG emissions, and energy by up to 13%, 8%, and 8%, respectively, compared to the non-optimal extreme cases. The extreme cases of "no wireless charging stations at all" and "wireless chargers at every bus stop" have higher impacts because the battery capacity can be large and expensive when there is no wireless charging stations at all and there is a trade-off of battery life and wireless charging infrastructure burden when there are chargers at every bus stop. There is no significant conflict among the three sustainability objectives so that a near-optimal deployment of wireless charging stations can achieve the three sustainability objectives almost simultaneously. For example, when planners optimally site the charging stations for the purpose of minimizing life cycle costs, they would almost achieve the minimal life cycle GHG emissions and energy consumption as well.

Further sensitivity and scenario analyses indicate that the conclusions are sensitive to the following parameters, assumptions, or calculations: (1) the initial battery unit price, (2) charging power rate, (3) charging infrastructure costs, (4) battery life calculation, (5) dwell time at bus stops, (6) social cost of carbon, and (7) variability of the electric grid in terms of prices, emissions, and energy inputs. Key observations include:

- With the objective of minimizing life cycle costs, fewer charging stops would be deployed if initial battery unit price is cheaper, charging power rate is higher, charging infrastructure costs are higher, or battery aging is slower.
- Bus dwell time plays an important role in determining whether or not to deploy the wireless charging infrastructure at certain bus stops.
- There would be more coverage of wireless charging infrastructure when more emphasis is put on the social cost of carbon emissions.
- The temporal variability of the electric grid in terms of carbon and energy intensities would also greatly trade off the cost objective with the GHG and energy objectives because of the difference in fuel profiles and energy demand between night hours and daily bus operation hours. An almost full coverage of wireless charging infrastructure at every bus stop would be favorable in terms of carbon emissions and energy consumption if the local electric grid is much cleaner and more energy efficient in the daytime than the nighttime.

This optimization model framework can be extended and adapted in different bus system settings by customizing route data (dwell time, route schedule, and bus stop information, etc.) to aid decision marking and strategic deployment of wireless charging technology in current or prospective electric bus projects around the globe. Bus systems in cities with more overlapping routes and shared bus stops (i.e., the utility of bus stops is high) than the Ann Arbor Blue Bus system would expect a lower fraction of burdens from the charging infrastructure to achieve the same level of wireless charging service. On the other hand, cities with a low charging station utility would expect a higher proportion of burdens from the charging infrastructure. The adaptation and application of this optimization model framework can enhance the sustainability performance of electric transit systems and facilitate the penetration of electrified mobility.

Appendix B Supporting information for Chapter 4

State of charge (SOC) curves for each route

The state of charge curves for each route at minimal life cycle costs are shown below.

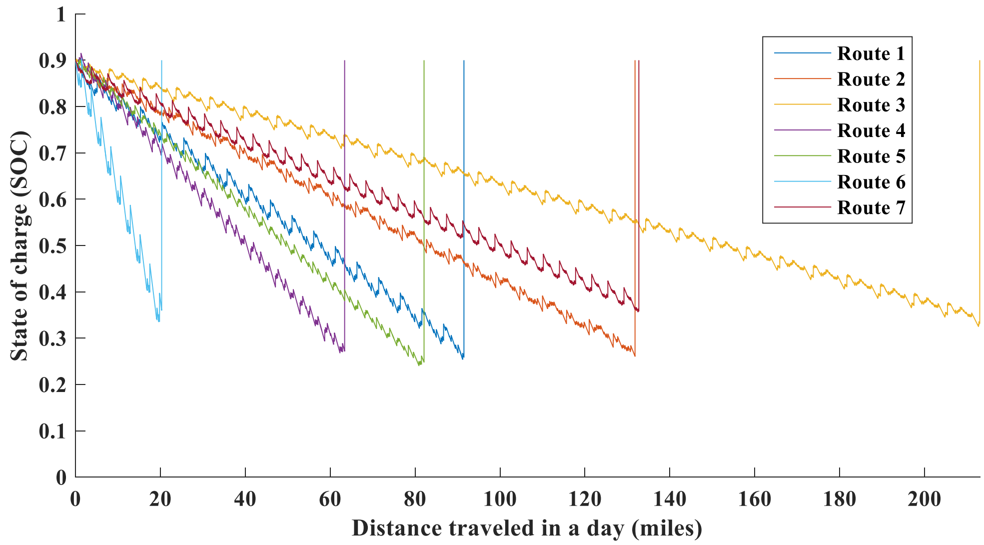


Figure 4.10 State of charge (SOC) curves for each route at life cycle cost optima. Note: 1 mile ≈ 1.609 km

Scenario analysis: Utility of bus stations

The base case results are shown in the main body of this chapter. Here are the results of the scenario analysis on the utility of bus stations. The single-objective optimization results when the utility of bus stations is increased to 1.75 routes per bus stop (the base case is 1.62 routes per bus stop) are shown below.

Table 4.3 Single-objective optimization results for a scenario of increased utility of bus stations

		Cost	GHG	Energy
Objective function ($, kg CO_2-eq, or MJ)		9,548,967	45,190,957	582,541,344
Number of stops selected out of 83 stops		36	48	45
Battery capacity (kWh)	Route 1	68	68	68
	Route 2	84	74	76
	Route 3	105	100	100
	Route 4	57	48	48
	Route 5	85	56	67
	Route 6	25	25	25
	Route 7	79	79	79
Battery life (years)	Route 1	6.6	6.6	6.6
	Route 2	6.5	6.5	6.5
	Route 3	6.6	6.5	6.5
	Route 4	7.3	6.9	6.9
	Route 5	7.8	6.8	7.3
	Route 6	8.6	9.9	9.9
	Route 7	6.8	6.8	6.8

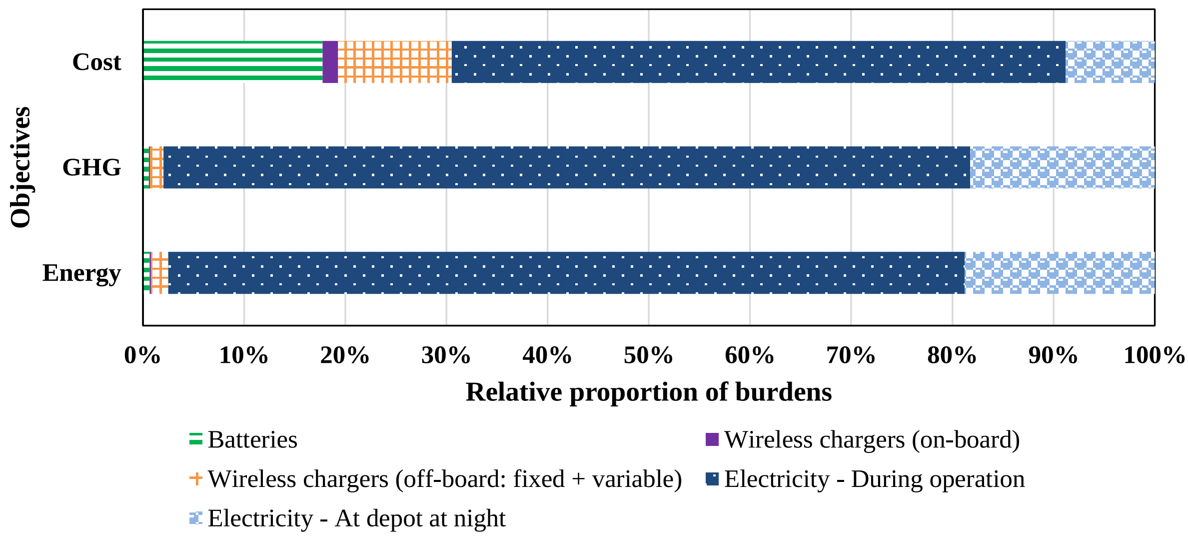


Figure 4.11 Breakdown of optimal life cycle burdens for the single objective of life cycle costs, greenhouse gas (GHG) emissions, and energy consumption for a scenario of increased utility of bus stations

Battery life sensitivity

The optimization results when using the energy-processed method for estimating battery life are shown in the table and figures below.

Table 4.4 Single-objective optimization results (when using the energy-processed method for estimating battery life)

		Cost	GHG	Energy
Objective function ($, kg CO_2-eq, or MJ)		9,270,706	45,049,855	580,926,259
Number of stops selected out of 83 stops		35	59	57
Battery capacity (kWh)	Route 1	68	44	47
	Route 2	98	60	60
	Route 3	168	100	100
	Route 4	57	46	46
	Route 5	85	54	54
	Route 6	29	25	25
	Route 7	97	65	88
Battery life (years)	Route 1	10.6	6.8	7.3
	Route 2	10.6	6.6	6.6
	Route 3	11.2	6.8	6.8
	Route 4	12.0	10.7	10.7
	Route 5	12.0	9.6	9.6
	Route 6	12.0	12.0	12.0
	Route 7	10.6	7.2	9.8

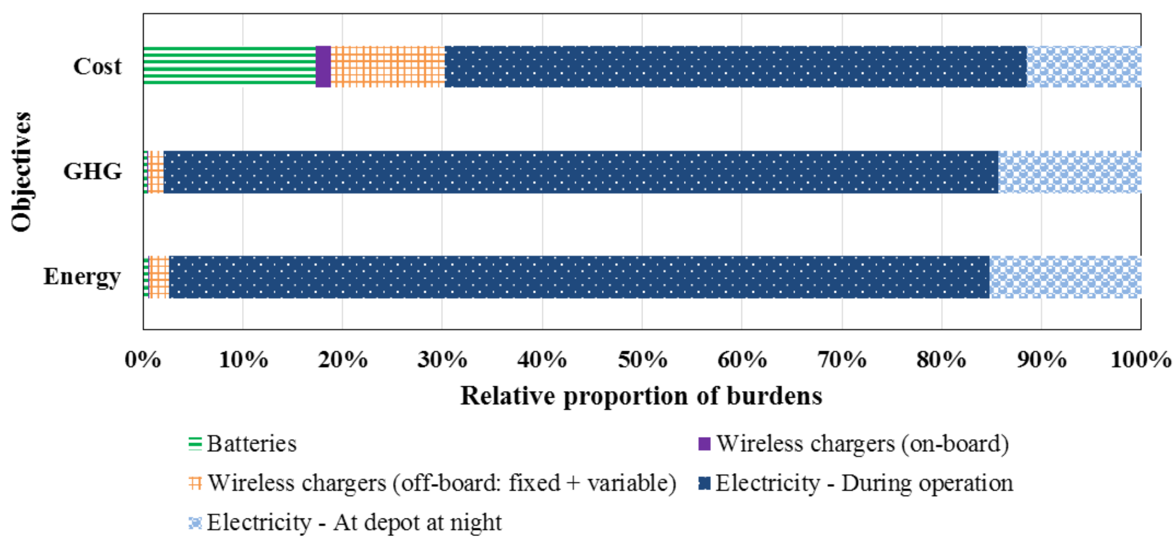


Figure 4.12 Breakdown of optimal life cycle burdens for the single objective of life cycle costs, greenhouse gas (GHG) emissions, and energy consumption (when using the energy-processed method for estimating battery life)

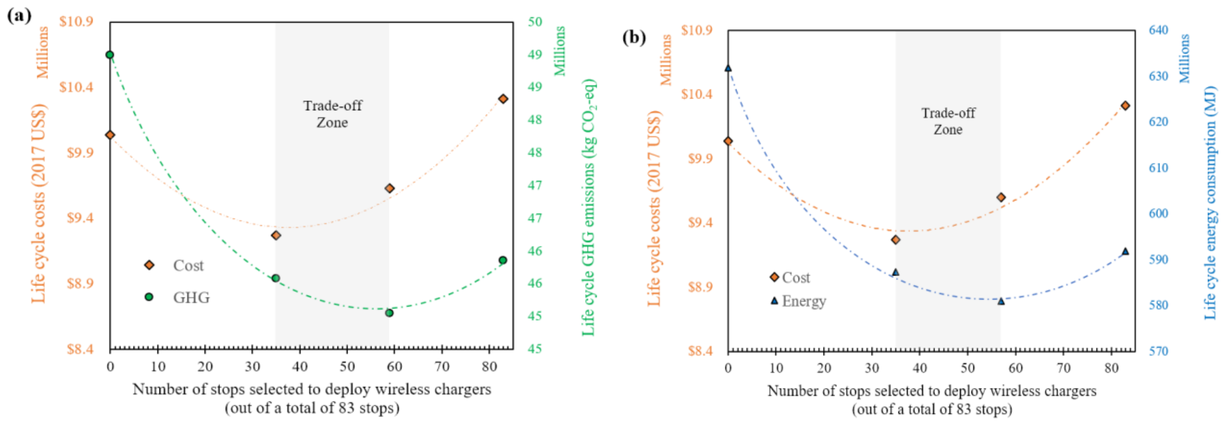


Figure 4.13 Multi-objective optimization (when using the energy-processed method for estimating battery life): (a) Cost and GHG objectives; (b) Cost and energy objectives. The trend lines for the objectives are polynomial approximations

References

[1] Hawkins TR, Gausen OM, Strømman AH. Environmental impacts of hybrid and electric vehicles—a review. Int J Life Cycle Ass 2012;17(8):997-1014.

[2] U.S. EPA. Inventory of U.S. greenhouse gas emissions and sinks: 1990-2011. Washington, DC, USA: U.S. Environmental Protection Agency; 2013.

[3] Davis SC, Diegel SW, Boundy RG. Transportation energy data book: Edition 33. Oak Ridge, Tennessee: Oak Ridge National Laboratory; 2014.

[4] Bi Z, Kan T, Mi CC, Zhang Y, Zhao Z, Keoleian GA. A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility. Appl Energ 2016;179:413-25.

[5] Miller JM, Jones PT, Li J-M, Onar OC. ORNL experience and challenges facing dynamic wireless power charging of EV's. IEEE Circ Syst Mag: IEEE; 2015. p. 40-53.

[6] Bi Z, Song L, De Kleine R, Mi C, Keoleian GA. Plug-in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. Appl Energ 2015;146:11–9.

[7] Bi Z, De Kleine R, Keoleian GA. Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system. J Ind Ecology 2016;21(2):344-55.

[8] Chen Z, He F, Yin Y. Optimal deployment of charging lanes for electric vehicles in transportation networks. Transport Res B 2016;91:344-65.

[9] Shahraki N, Cai H, Turkay M, Xu M. Optimal locations of electric public charging stations using real world vehicle travel patterns. Transport Res D 2015;41:165-76.

[10] Jang YJ, Suh ES, Kim JW. System architecture and mathematical models of electric transit bus system utilizing wireless power transfer technology. IEEE Syst J 2015;PP(99):1-12.

[11] Jeong S, Jang YJ, Kum D. Economic analysis of the dynamic charging electric vehicle. IEEE Trans Power Electron 2015;30(11):6368-77.

[12] Dunn JB, Gaines L, Sullivan J, Wang MQ. Impact of recycling on cradle-to-gate energy consumption and greenhouse gas emissions of automotive lithium-ion batteries. Environ Sci Technol 2012;46(22):12704-10.

[13] Clark NN, Zhen F, Wayne WS, Lyons DW. Transit bus life cycle cost and year 2007 emissions estimation. Washington, DC, USA: Federal Transit Administration; 2007.

[14] Cooney G, Hawkins TR, Marriott J. Life cycle assessment of diesel and electric public transportation buses. J Ind Ecology 2013;17(5):689-99.

[15] MathWorks Inc. Genetic algorithm, https://www.mathworks.com/help/gads/genetic-algorithm.html; 2015 [accessed January 2017].

[16] You S, Rasmussen CN. Generic modelling framework for economic analysis of battery systems. In: IET Conference on Renewable Power Generation (RPG 2011). IET; 2011. p. 1-6.

[17] U.S. EIA. Electricity data browser - Average retail price of electricity - Michigan - Transportation, http://www.eia.gov/electricity/data/browser/; 2016 [accessed Janurary 2017].

[18] DTE Energy. Electric service rates, https://www2.dteenergy.com/; 2015 [accessed Janurary 2017].

[19] U.S. EPA. Avoided emissions and generation tool (AVERT). U.S. Environmental Protection Agency (EPA) Office of Air and Radiation Climate Protection Partnerships Division; 2016.

[20] BYD Auto Company. 2013 BYD 40-ft electric bus specs, http://www.byd.com/la/auto/ebus.html; 2013 [accessed May 2014].

[21] Sathre R, Scown CD, Kavvada O, Hendrickson TP. Energy and climate effects of second-life use of electric vehicle batteries in California through 2050. J Power Sources 2015;288:82-91.

[22] Luo X, Wang J, Dooner M, Clarke J. Overview of current development in electrical energy storage technologies and the application potential in power system operation. Appl Energ 2015;137:511-36.

[23] Bayram IS, Tajer A. Plug-in electric vehicle grid integration. Norwood, MA: Artech House; 2017.

[24] Rosenkranz C. (Johnson Controls) at EVS 20, Long Beach, CA, November 15-19, 2003.

[25] Ko YD, Jang YJ. The optimal system design of the online electric vehicle utilizing wireless power transmission technology. IEEE Trans Intell Transp Syst 2013;14(3):1255-65.

[26] Kelly J, Ersal T, Li C, Marshall B, Kundu S, Keoleian G, et al. Sustainability, resiliency, and grid stability of the coupled electricity and transportation infrastructures: Case for an integrated analysis. J Infrastruct Syst 2015;21(4):04015001.

[27] U.S. EPA. The social cost of carbon. Washington, DC: U.S. Environmental Protection Agency (EPA); 2017.

CHAPTER 5

Life cycle assessment and tempo-spatial optimization of deploying dynamic wireless charging technology for electric cars

Abstract

Dynamic wireless power transfer (DWPT), or dynamic wireless charging technology, enables charging-while-driving and offers opportunities for eliminating range anxiety, stimulating market penetration of electric vehicles (EVs), and enhancing the sustainability performance of electrified transportation. However, the deployment of wireless charging lanes on highways and urban road networks can be costly and resource-intensive. A life cycle assessment (LCA) is conducted to compare the sustainability performance of DWPT applied in a network of highways and urban roads for charging electric passenger cars. The assessment compares DWPT to stationary wireless charging and to conventional plug-in charging using a case study of Washtenaw County in Michigan, USA over 20 years. The LCA is based on three key sustainability metrics: costs, greenhouse gas (GHG) emissions, and energy burdens, encompassing not only the use-phase burdens from electricity and fuel, but also the upfront deployment burdens of DWPT infrastructure. A genetic algorithm is applied to optimize the rollout of DWPT infrastructure both spatially and temporally in order to minimize life cycle costs, GHG, and energy burdens: (1) spatial optimization selects road segments to deploy DWPT considering traffic volume, speed, and pavement remaining service life (RSL); (2) temporal optimization determines in which year to deploy DWPT on a particular road segment considering EV market share growth as a function of DWPT coverage rate, future DWPT cost reduction, and charging efficiency improvement. Results indicate that optimal deployment of DWPT electrifying up to about 3% of total roadway lane-miles reduces life cycle GHG emissions and energy by up to 9.0% and 6.8%, respectively, and enables downsizing

of the EV battery capacity by up to 48%, compared to the non-DWPT scenarios. Roadside solar panels and storage batteries are essential to significantly reduce life cycle energy and GHG burdens but bring additional costs. Breakeven analysis indicates a breakeven year for solar charging benefits to pay back the DWPT infrastructure burdens can be less than 20 years for GHG and energy burdens but longer than 20 years for costs. A monetization of carbon emissions of at least \$250 per metric tonne of CO_2 is required to shift the optimal "pro-cost" deployment to the optimal "pro-GHG" deployment. A roadway segment with volume greater than about 26,000 vehicle counts per day, speed slower than 55 miles per hour (1 mile ≈ 1.609 km), and pavement RSL shorter than 3 years should be given a high priority for early-stage DWPT deployment.

5.1 Introduction

This chapter evaluates the economic, environmental, and energy performance of wireless charging EVs and wireless charging infrastructure systems from a life cycle assessment (LCA) perspective. LCA provides a holistic view of technology deployment, encompassing not only the use-phase energy use, but also the burdens of infrastructure and equipment deployment necessary for the system. A broad LCA scope is important to objectively evaluate the emerging technology because wireless charging technology has trade-offs between infrastructure deployment burdens and use-phase benefits. This study establishes LCA models and creates scenarios to understand under what conditions or scenarios wireless-charging-based transportation systems could have better life cycle performance compared to plug-in charging systems in terms of costs, GHG, and energy.

A highlight of this LCA study is that the deployment of DWPT infrastructure is optimized both spatially and temporally. This study features not only the spatial optimization of DWPT charging lanes studied in literature [1, 2] showing that optimized deployment on key highways and urban roadways can electrify the majority of vehicle miles traveled (VMT) in a region, but also has a unique temporal optimization component for the gradual rollout of the DWPT infrastructure, which is usually overlooked in the literature. This optimization analysis aims to understand how to deploy DWPT considering spatial and temporal variations with objectives of minimizing life cycle costs, GHG, and energy:

- *Spatial optimization component.* This study studied the spatial optimization of DWPT charging lanes on highways and urban roadways, i.e., which road segments are selected for charging lane deployment. Three major characteristics or parameters of the roadway segments are considered: (1) traffic volume; (2) vehicle speed; and (3) remaining service life (RSL) of pavement, which quantitatively reflects the pavement condition. In general, a road segment with high volume, low speed, and poor condition is preferred for initial deployment as it will generate a high electrified VMT which means a high utilization rate of the deployed infrastructure, and also will reduce the burdens of charging lane deployment as it is more likely to deploy at the same time of scheduled pavement reconstruction and rehabilitation work.
- *Temporal optimization component.* This study also focuses on the temporal optimization of DWPT infrastructure rollout, i.e., in which year to deploy wireless charging lanes at each road segment. There are four major considerations: (1) EV sales; (2) costs of wireless charging infrastructure and battery; (3) wireless charging efficiency; and (4) battery downsizing. In general, DWPT deployment is good for boosting EV sales [3] more than business-as-usual so that the benefits of EVs can be realized sooner and it is also good for downsizing the battery and lightweighting the vehicle [4]. In contrast, later deployment is good when considering that DWPT and battery costs would both be cheaper and charging efficiency would be higher due to mass production and technology improvement.

The novel contribution of this chapter is the combined spatial and temporal optimization utilizing the holistic LCA scope to evaluate the performance of wireless charging under different scenarios and to provide guidance for DWPT deployment. The spatial optimization of selecting roadway segments considers traffic volume, speed, and pavement condition, and the temporal optimization of "when to deploy" considers cost reduction, technical improvement of wireless charging technology in the future, and EV market share growth as a function of DWPT coverage rate. To the best of authors' knowledge, it is also the first study using real-world traffic counts data for each segment of highways and urban roads [5] to evaluate life cycle performance of wireless charging technology deployment. The model is demonstrated using a case study of arterial roads in Washtenaw County in Michigan, USA.

5.2 Methods

5.2.1 Overview of system and scenarios

LCA has been conducted to evaluate the life cycle costs, GHG, and energy of a transportation system within a bounded geographical region, e.g., a county, over a period of 20 years, including infrastructure deployment and vehicle operation. Twenty years is assumed based on the expected lifetime of both DWPT infrastructure and pavement [6]. The characteristics of the transportation system are defined as follows.

Functional unit and system boundary. The total VMT associated with arterial roads within a bounded geographical region serves as the functional unit of this LCA. Therefore, calculations and results of costs, GHG, and energy of infrastructure, chargers, battery, and electricity burdens are all based on the total VMT. Other types of VMT, including the VMT associated with non-arterial (including rural roads) and the VMT outside the geographical boundary, are not incorporated.

Vehicles. The vehicles in this transportation system are passenger cars. Trucks are excluded. In terms of powertrain, the vehicles are composed of the conventional internal combustion engine vehicles which run on gasoline (referred to as "gasoline/ICE vehicles" in this study) and fully electric vehicles (EVs) which run on electricity charged from the electricity grid and/or roadside solar panels deployed along the roads. Hybrid vehicles, including PHEVs, are not incorporated for model simplicity. The share of EVs within all vehicles varies by year as a function of the coverage rate of DWPT on the roadways. The battery and charging equipment are the major differences between ICE vehicles and EVs in terms of cost, GHG, and energy burdens at materials production and manufacturing stages. Therefore, the EV battery and charging equipment are incorporated, but the vehicle body of ICE vehicles and EVs is assumed to have comparable burdens thus excluded in the system, based on previous LCA of vehicles [4, 7]. As one of the main battery chemistries considered for EV applications, the $LiFePO_4$ battery is chosen as the battery chemistry for this study. EVs are assumed to be equipped with on-board wireless charging pads, enabling wireless charging as long as they are on DWPT-enabled lanes. Although there are variations in energy efficiencies at different speed levels of EVs and ICE vehicles, constant fuel economies are assumed in this study for highway and city driving respectively for each type of vehicle, which are adequate to capture the system-level performance of the entire vehicle population given the purpose of this study.

Roadways. Arterial roads, including interstate highways and major urban roadways, are potential candidates for DWPT deployment, given their high capacity and utilization. The definition of arterial roads varies from country to country, or even state to state and city to city, so it depends on each specific case study. Although rural roads take up 60% of total roadway miles in the U.S., the VMT on rural roads are only 14%, compared to 86% for interstate and urban roadways [2]. The arterial roads are segmented to facilitate the modeling of LCA and optimization. Highways are segmented based on entry and exit; urban roadways are segmented based on traffic intersections. The coverage rate of DWPT deployment is defined as the lane-miles of roadways with DWPT versus the total lane-miles in the region.

Charging infrastructure. The DWPT infrastructure includes the electric grid power delivery infrastructure (feeder & connecting wires), WPT electronics (inverters, transformers, and coils), and roadway retrofitting (pavement), as shown in Figure 5.1.

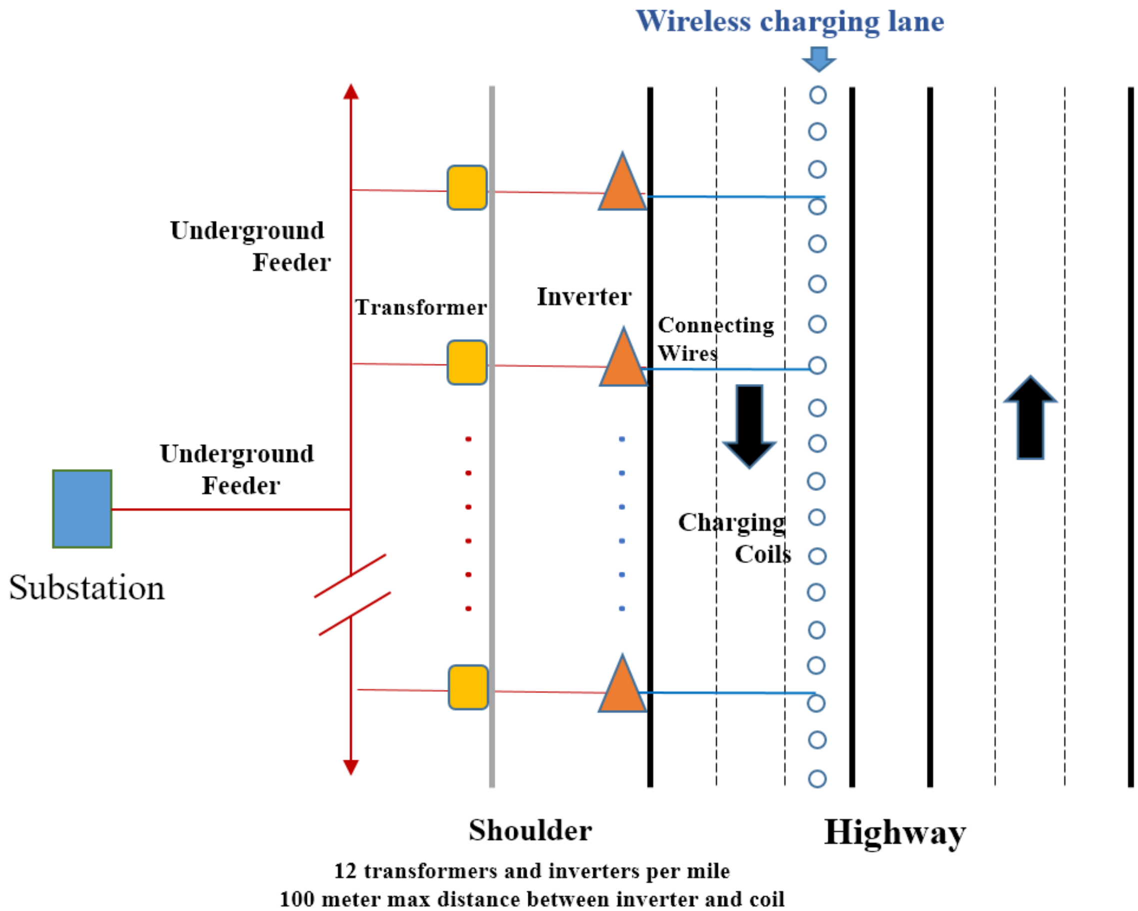


Figure 5.1 Schematic of dynamic wireless charging infrastructure. The figure is adapted based on a previous study [8]

A case study of Washtenaw County in Michigan is conducted based on the definition of the transportation system described above. The following arterial roads are segmented: I-94 East, I-94 West, US-23 North, US-23 South, M-14 East, M-14 West, US-12 East, US-12 West, M-52 North, M-52 South, I-94BL/M-17 East, and I-94BL/M-17 West. These roads are representative of highways and urban roads with varying speed limits from 25 to 70 miles per hour (1 mile ≈ 1.609 km). The traffic volume throughout 24 hours of a day is based on the traffic count data from Traffic Monitoring Information System (TMIS) by Michigan Department of Transportation (MDOT) [5]. This 24-hour resolution instead of a daily average volume helps determine the GHG emissions and energy of wireless charging because the electricity grid has varying emission and energy intensities throughout the day due to different dispatch of power plants to meet the varying power demand. The GHG (kg CO_2-eq/kWh) and energy (MJ/kWh) intensity values varying throughout the day are obtained from the AVoided Emissions and geneRation Tool (AVERT) developed by U.S. Environmental Protection Agency (EPA) [9]. The traffic speed is based on the speed limit of each roadway segment. The remaining service life (RSL) data are obtained from the Pavement Management System by MDOT [10].

Based on the definition of the transportation system, a total of eleven scenarios are created in order to provide a life cycle comparison of DWPT versus SWPT and plug-in charging technology, as defined in Table 5.1. Scenarios vary by whether or not they have the following components: (1) Plug-in charging (PC) at home/public parking; (2) stationary wireless power transfer at home/public parking (SWPT-H/P); (3) stationary wireless power transfer at traffic lights (SWPT-Lights); (4) dynamic wireless power transfer (DWPT) on arterial roads; (5) roadside solar panels and storage batteries (denoted as "Solar"); (6) EV sales boosted by DWPT deployment (denoted as "EV sales boost"), otherwise it is business-as-usual with the base projection of EV market growth; (7) Grid & fuel: whether it is using the electricity grid and fuel from Michigan (MI) or California (CA). For the scenarios with DWPT, the DWPT deployment is optimized both spatially and temporally, which is described in detail in Section 5.2.2. For the scenarios with roadside solar panels and storage batteries as electricity sources for charging EVs moving on the roadway, the calculation of solar panel size and roadside storage battery capacity is given in the Appendix. The scenarios denoted with "CA" evaluate what if the system defined in Washtenaw County uses the cleaner and less energy-intensive electricity as in the California grid instead of the Michigan grid, and uses the lower transportation electricity price and the higher gasoline price in California instead of Michigan.

Table 5.1 Description of scenarios

Scenario number and name	*PC*	*SWPT-H/P*	*SWPT-Lights*	*DWPT*	*Solar*	*EV sales boost*	*Grid & fuel*
1. PC	✓	-	-	-	-	-	MI
2. SWPT-H/P	-	✓	-	-	-	-	MI
3. SWPT-H/P + SWPT-Lights	-	✓	✓	-	-	-	MI
4. SWPT-H/P + DWPT	-	✓	-	✓	-	✓	MI
5. SWPT-H/P + DWPT + SWPT-Lights	-	✓	✓	✓	-	✓	MI
6. SWPT-H/P + DWPT + Solar	-	✓	-	✓	✓	✓	MI
7. SWPT-H/P + DWPT + SWPT-Lights + Solar	-	✓	✓	✓	✓	✓	MI
8. SWPT-H/P + DWPT + SWPT-Lights + CA	-	✓	✓	✓	-	✓	CA
9. SWPT-H/P + DWPT + Solar + CA	-	✓	-	✓	✓	✓	CA
10. SWPT-H/P + DWPT + SWPT-Lights + Solar + CA	-	✓	✓	✓	✓	✓	CA
11. SWPT-H/P + DWPT + SWPT-Lights + Base EV Growth	-	✓	✓	✓	-	-	MI

Notes: "✓" = "There is"; "-" = "There is not"; PC = plug-in charging; SWPT-H/P = stationary wireless power transfer at home/public parking; SWPT-Lights = stationary wireless power transfer at traffic lights; DWPT = dynamic wireless power transfer; Solar = roadside solar panels and storage batteries; EV = electric vehicle; MI = Michigan electricity grid and fuel; CA = California electricity grid and fuel

The GHG and energy burdens of wireless charging infrastructure are based on the life cycle inventory (LCI) analysis conducted by the authors [4]. The metric of GHG emissions is used to evaluate environmental performance in this study. Other emissions, such as criteria air pollutants of SO_x and NO_x, can also be studied in future work based on the LCI. The detailed LCI, including GHG emissions, criteria air pollutants, and energy of deployment of one lane-mile of DWPT, can be found in the Appendix.

5.2.2 Life cycle optimization of DWPT deployment

The DWPT deployment is optimized both spatially and temporally for each of the scenarios with DWPT as described in Section 5.2.1. In this section, a summary of the optimization problem is provided, including the optimization objectives, decision variables, solving method, constraints, and highlighted novelty. Details of the model formulation, including the equations and parameters, are in the Appendix.

Objectives. The optimization problem is formulated and solved respectively for the following three distinct objectives: (1) minimize life cycle costs on a present-value basis; (2) minimize life cycle GHG emissions; and (3) minimize life cycle energy. The optimization aims to minimize the life cycle burden (costs, GHG, or energy) in a 20-year period for the transportation system defined in Section 5.2.1, by selecting where (i.e., at which segment of roadway) and when (i.e., in which year) to deploy the wireless charging infrastructure. The objective function F is defined as below, which is the sum of life cycle burdens from eleven components φ_s ($s = 1, 2, ..., 11$), including DWPT and SWPT infrastructure, solar infrastructure, EV batteries, and use-phase energy consumption, etc. The life cycle burden F can be life cycle cost (U.S. $), GHG (kg CO_2-eq), or energy (MJ) burdens, depending on the objective currently under evaluation. Details can be found in the Appendix.

$$F = \sum_{s=1}^{11} \varphi_s \qquad \text{(Eq. 5.1)}$$

Decision variable and solving method. The decision variable is a vector in which each element represents a road segment and has a value from 1 to 20 indicating the year of deployment for each road segment or a value of 0 if a road segment is not selected for wireless charger deployment in any year within the 20-year period. The decision variable vector is solely composed of integers so the optimization problem is an integer programming problem. A heuristic genetic algorithm (GA) solver [11] is used to find a near-optimal solution for the model, because of the nonlinearity and complexity (e.g., the temporal variations of EV market share in response to DWPT deployment) and large decision space (i.e., deciding which year during the 20 years to deploy DWPT for each of 154 segments of roadways) of this discrete optimization model. GA is not guaranteed to find a global optimal solution because the algorithm is heuristic, but the near-optimal solutions obtained by GA are adequate for the purpose of this study as it aims to demonstrate the utility of the model framework, illustrate the tradeoffs and interactions between model elements, and compare and identify the scenarios under which wireless charging can help reduce life cycle costs, GHG, and energy. Therefore, the term "optimal" refers to "near-optimal" in this study. The objective F is a function of the decision variable vector $\boldsymbol{X}''$ defined below (details can be found in the Appendix), indicating the year of deployment of DWPT ($x''_j = 1, 2, 3, ..., 20$) or no deployment in any year ($x''_j = 0$) for each road segment *j*.

$$\boldsymbol{X}'' = \left\{ x''_j \mid x''_j = 0, 1, 2, 3, ..., 20 \right\} \quad j = 1, 2, ..., 154 \qquad \text{(Eq. 5.2)}$$

Constraints. The constraints of this optimization problem include the following: (1) Each element in the decision variable vector has to be an integer ranging from 0 to 20; (2) To limit the length of DWPT lanes deployed per year, the total annual expense for deploying DWPT on selected road segments should not exceed a pre-defined budget allocated to the DWPT deployment from the transportation administrative agency, which is assumed to be $30 million per year for the base scenario to pay for road retrofitting work that is directly related to DWPT deployment, DWPT electronics, and connecting to the electricity grid including labor costs. This estimated budget level is based on one-to-one match of the current Michigan Department of Transportation (MDOT) average budget for road repair work [12]. The budget level is varied in a sensitivity analysis in order to show its effect on DWPT deployment. The constraint is defined as below, limiting the annual deployment of DWPT infrastructure θ_i (U.S. $) within the annual budget c_i (U.S. $) for year *i*. Details can be found in the Appendix.

$$\theta_i \le c_i \text{ for } \forall i \in \{1, 2, ..., 20\} \quad \text{(Eq. 5.3)}$$

A highlight of this charging infrastructure optimization problem is that it not only optimizes the spatial deployment as many other spatial-only optimization studies [1, 13-16], but also has a temporal component for deciding which year to roll out DWPT lane for each road segment considering the year-by-year variations of various model parameters. The tempo-spatial optimization characteristics are described below:

Spatial variations. The decision variable vector specifies which segments of roadways are selected for DWPT deployment if its value is non-zero (i.e., 1 to 20). In order to determine whether or not to deploy DWPT, it is necessary to differentiate the road segments based on these three metrics: (1) traffic volume; (2) vehicle speed; and (3) remaining service life (RSL) of pavement, which quantitatively reflects the pavement condition. In general, deploying DWPT lanes on road segments with a high traffic volume means a great number of VMT can be electrified. The more VMT is electrified by clean electric energy, the more cost, GHG, and energy benefits arise. Similarly, if two road segments have similar traffic volumes but one has a lower average vehicle speed than the other, then the lower-speed road segment is preferred because it can charge more electricity to the vehicle in a fixed distance. Lastly, the RSL of pavement is also affecting the decision of where to deploy DWPT. For example, if a road segment has a short RSL of 2 years, it means this segment is in poor pavement condition that requires road repair soon. If the DWPT deployment happens to be the same year of the scheduled road repair work, then there will be some credits because some of the deployment costs and pavement material burdens can be saved as the

DWPT deployment is in conjunction with the road repair. For another example, however, if the DWPT deployment happens earlier than the scheduled road repair, then there will be a penalty proportional to pavement burden because a "good" road will be replaced earlier than its service life.

Temporal variations. The decision variable vector also indicates the year of deployment if a road segment is selected for DWPT deployment. There are four major considerations: (1) EV sales; (2) costs of wireless charging infrastructure and battery; (3) wireless charging efficiency, and (4) battery downsizing and battery life. Details of each temporal variation are given below.

(1) EV sales. Based on the Market Acceptance of Advanced Automotive Technologies (MA3T) model developed by Oak Ridge National Laboratory (ORNL) [3], the EV sales share in a given year is boosted as a function of the coverage percentage of DWPT infrastructure on roadways. The generalized boost function can be found in the Appendix. In each iteration of optimization, given a specified decision variable, the model is able to calculate the EV sales share growth from year 1 to year 20 based on the functional relationship to the DWPT coverage rate, and then translate the sales share of EVs to the total cumulative share of EVs in all vehicles in operation in any given year by considering the average lifetime of a vehicle (eleven years) [17]. Therefore, the more DWPT coverage, the more ICE vehicles will be replaced by EVs. Two additional related assumptions are stated as follows. (a) Only one lane in each direction is assumed to be renovated as DWPT lanes. When the EV market share is high and a large amount of EVs are crowded on the DWPT lanes, if an EV cannot get the charge at a particular road segment due to congestion in the charging lane, it is assumed to get equivalent charges elsewhere (e.g., other DWPT segments). Also smart regulation of EVs and autonomous vehicular technology can help prevent this issue by allowing EVs with urgent charging demand (i.e., low state of charge) to charge first. (b) Only DWPT, not SWPT at traffic lights, would be able to boost EV sales. Although SWPT at traffic lights is assumed to be gradually rolling out following a linear growth pattern from 0% to 25% of total traffic intersections in the region, the scale of SWPT infrastructure is much smaller compared to DWPT and is usually condensed in urban areas (e.g., downtown). Therefore, SWPT at traffic lights alone is assumed to have negligible impact on relaxing the range anxiety and not sufficient to boost EV market share growth.

(2) Costs of wireless charging infrastructure and battery. The cost of DWPT deployment at year 1 is assumed to be \$2.5 million per lane-mile (1 mile ≈ 1.609 km) [8, 18, 19]. The future cost of DWPT is assumed to follow a learning curve with a learning rate of 20%, which means the cost of DWPT decreases by 20% for every doubling of cumulative production or deployment. It is assumed to be similar to the cost reduction of solar panels because their major components are electronics [20]. Therefore the cost of DWPT is assumed to decrease from \$2.5 million/lane-mile in year 1 to about \$1 million/lane-mile in year 20. SWPT is assumed to follow the same learning rate based on its market prices [21, 22]. The EV lithium-ion battery cost is assumed to be \$500/kWh in year 1 and decrease by 4.4% per year and reach \$213/kWh at year 20 based on market projections [23]. Additionally, the roadside storage battery is assumed to follow the same cost reduction curve as the EV battery.

(3) Wireless charging efficiency. The grid-to-battery wireless charging efficiency is currently around 85% to 90% for SWPT and 72% to 83% for DWPT, as compared to 90% for plug-in charging [18]. Despite that there can be misalignment of charging pads which would further lower the charging efficiency, a 75% dynamic wireless charging efficiency in year 1 is used and this efficiency is assumed to increase by 0.5% per year and reach 84.5% in year 20, assuming autonomous vehicles in the future can help vehicle alignment to achieve good efficiency and technical advancements in wireless charger design and control can also help improve the charging efficiency. The electricity charged is calculated by multiplying wireless charging efficiency, battery efficiency, charging power rate (kW), and charging time (hours).

(4) Battery downsizing and battery life. The average battery capacity of the entire EV population in a given year is expected to decrease as a function of DWPT coverage increase, because EVs with wireless charging availability will depend less and less on the large onboard battery to store sufficient electricity for daily travel. A downsized battery can lead to a lightweight vehicle thus improve the fuel economy of the vehicle. The relationship of wireless charger deployment, battery downsizing, and fuel economy improvement was defined by the authors previously [4]. Given a downsized battery and reduced energy demand, the corresponding battery life is estimated using the experiment-based energy-processed model [24], which specifies the cumulative energy processed of each cell in a battery pack at retirement when 20% of battery nameplate capacity is lost. Even though each cell in a downsized battery processes more electricity

thus degrades faster according to the energy processed model, the use-phase lightweighting benefits of battery downsizing may offset some or all of the additional battery burdens resulting from compromised battery life. Details can also be found in the Appendix.

Therefore, in general, DWPT deployment is expected to boost EV sales more than business-as-usual so that the environmental and energy benefits brought by the EVs can be realized sooner. Also, with more DWPT coverage, the average battery capacity is expected to be smaller to travel a required distance and a smaller battery would be able to lightweight the vehicle and improve fuel economy [4]. However, later deployment has benefits when considering that DWPT and battery costs would both be lower and charging efficiency would be higher due to mass production and technology improvement.

5.3 Results

5.3.1 Life cycle costs, GHG emissions, and energy results of different scenarios

The LCA results comparing different scenarios of EV charging, as previously defined in Table 5.1, are presented in this section. The life cycle burdens in terms of costs, GHG emissions, and energy are shown in Figure 5.2. The corresponding optimal DWPT coverage growth curves for each scenario with DWPT, along with their battery downsizing, are shown in Figure 5.3.

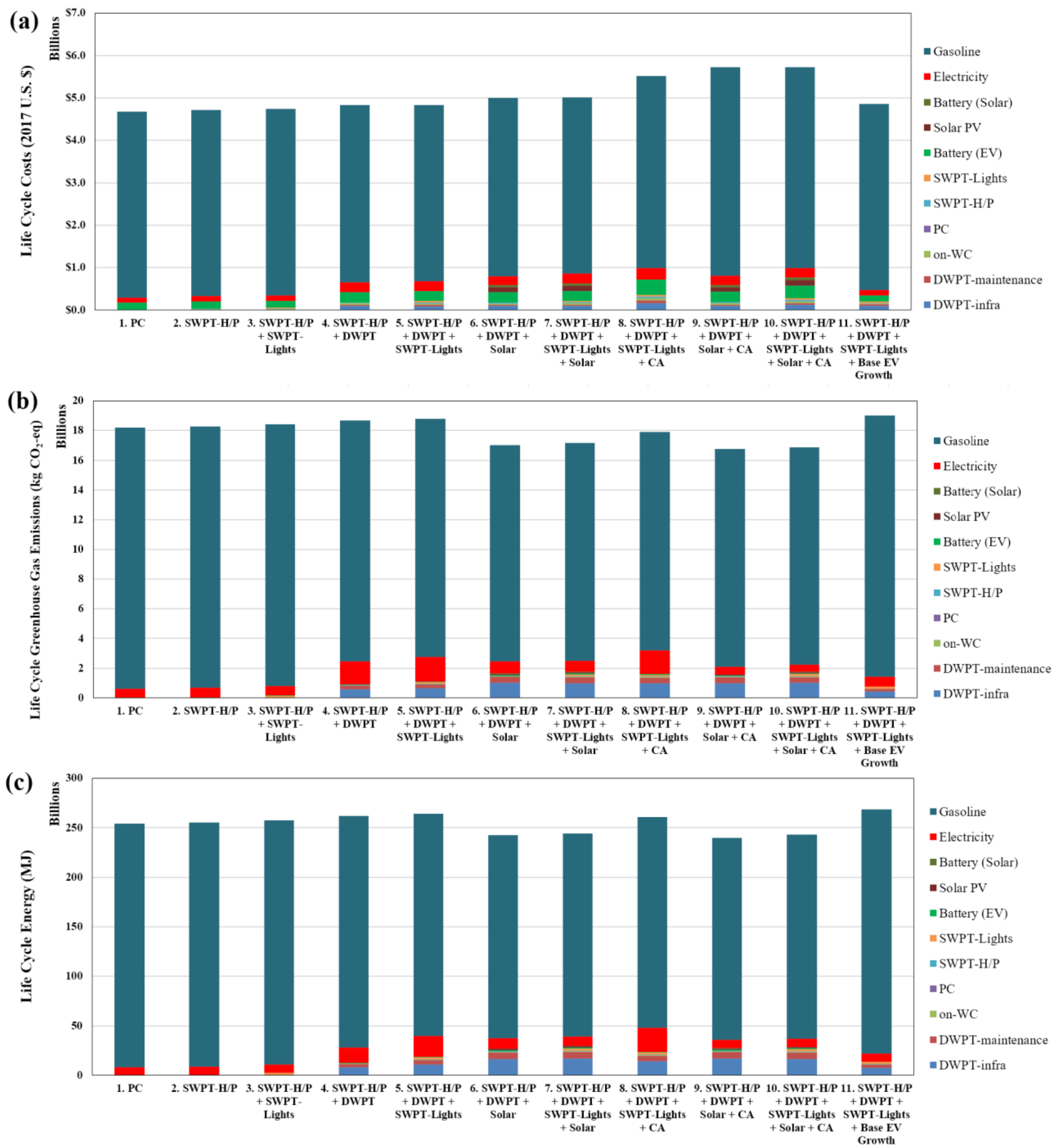


Figure 5.2 Comparison of eleven scenarios: (a) life cycle costs (in 2017 present-value dollars); (b) life cycle greenhouse gas emissions; and (c) life cycle energy. Note: on-WC = on-board wireless charger installed on the vehicle

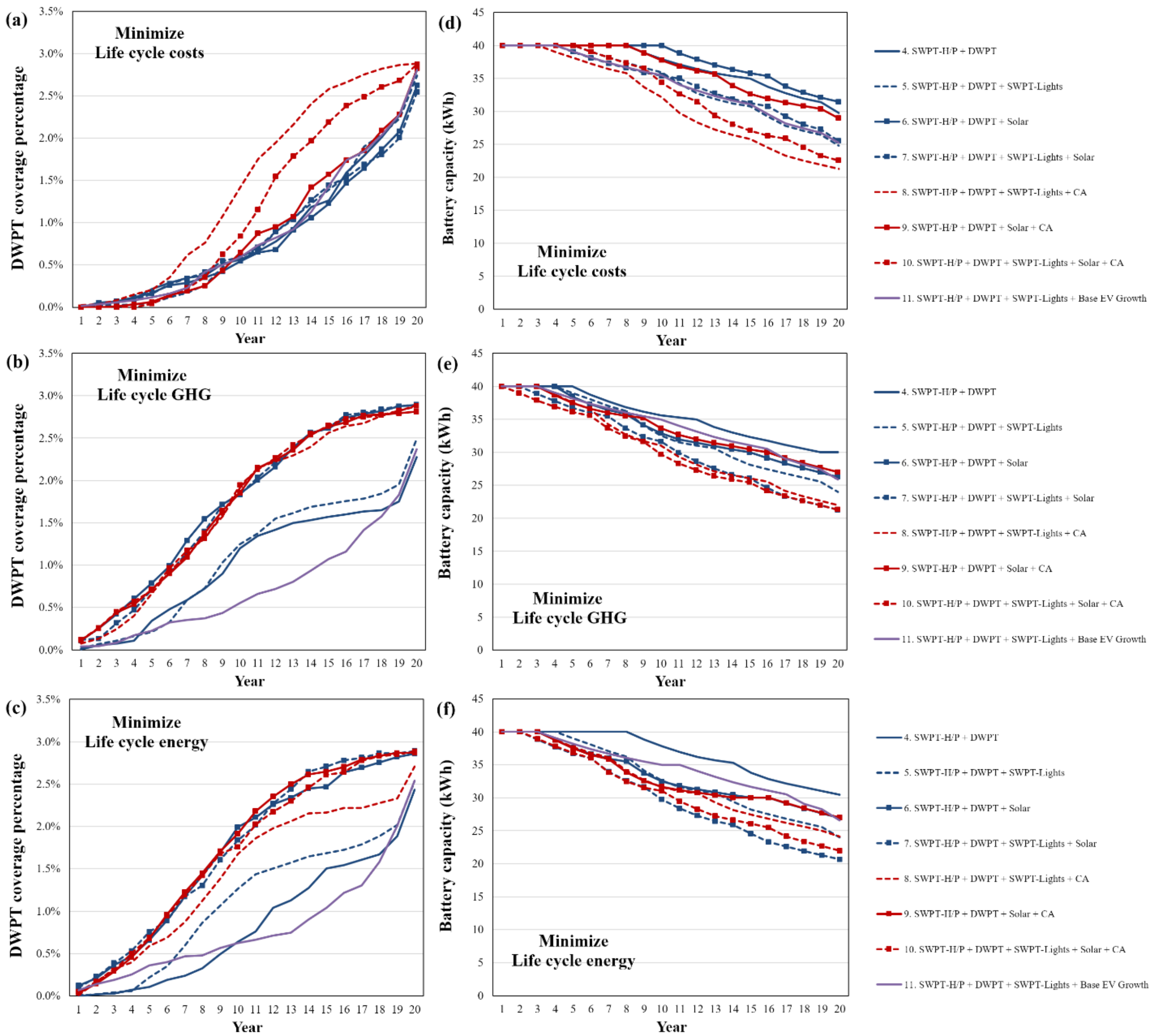


Figure 5.3 Optimized deployment coverage growth for each scenario with dynamic wireless charging infrastructure, as well as the corresponding battery downsizing trends. Note: GHG = greenhouse gases; and DWPT = dynamic wireless power transfer

By observing these scenario results and comparing the scenarios with DWPT (scenarios #4 to #11) to the scenarios without DWPT (scenario #1 to #3), the following observations can be made:

(1) Deployment of DWPT infrastructure reduces life cycle GHG emissions and energy by up to 9.0% and 6.8%, respectively, compared to the non-DWPT scenarios under either or both of the following conditions: (a) solar panels and storage batteries are present as electricity sources for EV charging along roadways; (b) the regional electricity grid has low carbon and energy intensities,

e.g., the California grid (0.477 kg CO_2/kWh and 8.353 MJ/kWh on average) is lower than the Michigan grid (0.759 kg CO_2/kWh and 9.739 MJ/kWh on average) [9]. Note that the GHG and energy graphs share similar patterns as GHG emissions are usually proportional to energy consumption [4].

(2) Deployment of DWPT infrastructure would not reduce life cycle costs, especially when solar panels and storage batteries are present along roadways as electricity sources for EV charging. Despite the fact that the availability of solar energy as an electricity source for charging moving EVs on roadways can reduce life cycle GHG emissions and energy burdens, the infrastructure costs from the solar panels and storage batteries would bring additional costs to the already expensive DWPT infrastructure. The California scenarios have higher life cycle costs mainly because of the higher gasoline prices in California than in Michigan [25, 26].

(3) The larger-scale early deployment of DWPT is observed for GHG and energy objectives relative to the cost objective, which triggers faster growth of EV market penetration. Therefore, when prioritizing GHG and energy as the main design objectives, earlier and more aggressive deployment is generally preferable; when prioritizing costs, later deployment is desired. Note that in Figure 5.3 (b) and (c) the aggressive deployment scenarios are capped by the annual budget that limits the total lane-miles of DWPT infrastructure deployed per year. By relaxing the annual budget constraint, slightly more aggressive deployment would be expected. The sensitivity analysis on annual budget constraint is discussed in Section 5.4.1.

(4) Roadside solar panels and storage batteries are essential for significantly reducing life cycle GHG and energy burdens. The scenarios with availability of roadside solar energy as a source for charging moving EVs on roadways (scenarios #6, #7, #9, and #10) reveal significant reduction in life cycle GHG and energy burdens. Therefore, it is recommended to deploy roadside solar energy equipment together with DWPT when the design objective is prioritizing life cycle GHG emissions and energy burdens, however, this will increase infrastructure costs.

(5) Earlier and more aggressive deployment is preferred for states or regions with cleaner electricity than Michigan, e.g., California. As seen from Figure 5.3 (a) – (c), the scenarios assuming California grid and fuel instead of Michigan tend to have earlier and more aggressive deployment so that the benefits of cleaner electricity and lower transportation electricity price can be realized sooner by more EVs.

(6) Electrification of up to about 3% of total roadway lane-miles in the region by deployment of DWPT would significantly help downsize the EV onboard battery capacity by 21% to 48% as compared to the battery capacity of 40 kWh for the plug-in charging scenario. The downsizing of the EV battery can also help lightweight the vehicle and slightly improve the fuel economy, i.e., the energy consumption rate slightly decreases from 0.312 kWh/mile to 0.297 kWh/mile (1 mile ≈ 1.609 km). Because battery downsizing significantly reduces the number of cells in a battery pack while the energy consumption of EVs reduces only slightly, each cell in a downsized battery pack will take on more burden and process (i.e., charge and discharge) more electricity than the original battery so that the fleet-wide theoretical battery life would be shorter, based on the estimation of battery life using the energy-processed model [24]. However, the majority of theoretical battery life modeled in the eleven scenarios during the time period is still expected to exceed the vehicle life of eleven years due to the long cycle life of a $LiFePO_4$ battery. These batteries are assumed to retire at the same time as vehicle retirement, so the actual battery life is capped and counted as eleven years in this LCA study (for those batteries with shorter theoretical life than vehicle life in certain scenarios, partial burdens from replaced battery cells are also counted). The curves for changes in energy consumption rate of EVs and theoretical battery life can be found in the Appendix.

(7) Deployment of SWPT at traffic lights has negligible impacts on the life cycle costs, GHG emissions, and energy burdens. Deployment of SWPT at traffic lights has the benefit of further downsizing the battery because of more en-route charging time, but the additional burdens from the SWPT infrastructure itself would offset the benefit, resulting in almost unchanged life cycle burdens.

(8) The cost of GHG mitigation is $556 per tonne of mitigated GHG, by comparing costs and GHG emissions of scenario #2 and scenario #6 at minimal life cycle GHG emissions. It means an extra $556 is needed to pay for each tonne of GHG mitigated compared to the non-DWPT scenario. This carbon mitigation cost is much higher than the current social cost of carbon (SCC) varying from $11 to $212 per metric tonne of CO_2 estimated by an interagency study reported by the U.S. Environmental Protection Agency (EPA) [27], which means a stronger policy is needed to incentivize the DWPT deployment. It also means technology innovation is needed to reduce DWPT deployment costs. More discussion of SCC is provided in the Discussion Section.

(9) The DWPT infrastructure deployment and maintenance take up 2.3%-4.2%, 3.2%-8.4%, and 4.1%-10.0% of life cycle costs, GHG, and energy, respectively, depending on the scenarios.

5.3.2 Deployment strategies for DWPT

Deployment of DWPT infrastructure is a long-term, logistics-demanding, and resource-intensive process. Therefore, it is useful to prioritize candidate roadway segments and develop smart deployment strategies to allocate the limited annual budget to the highest priority candidates each year.

The optimization model informs decision makers on the recommended year to deploy a certain type of roadway segment based on the VMT, speed, and RSL of the segment for each objective of life cycle costs, GHG, or energy. It is observed that road segments with high VMT, low speed, and short RSL tend to be deployed with DWPT in early stages. The recommended years of DWPT deployment for each type of road segments based on the observed deployment rule are provided in Figure 5.4. The numbers in the figure indicate the average of deployment years for all segments in the respective categories. From a temporal point of view, the optimal deployment years for the life cycle cost objective are generally later than the life cycle GHG and energy objectives. From the spatial point of view, the results follow the rule that higher VMT, lower speed, and shorter RSL are preferable conditions for initial deployment of DWPT infrastructure. Deploying DWPT on road segments with high VMT means that a high percentage of miles traveled by EVs can be electrified. A lower speed also means more electricity can be charged to the EVs because it takes longer for the EVs to travel the same distance so that the charging time is extended. It is also wise to prioritize those segments with short RSL of pavement because these segments may need repair or reconstruction soon so that the DWPT deployment and routine road repair work can be conducted concurrently. Picking those segments with long RSL first during initial deployment is discouraged as it means tearing up relatively good condition roads earlier than their design service life. In this optimization model, a proportional penalty of costs, GHG, or energy based on pavement burden is applied if a segment is renovated for DWPT deployment earlier than its RSL.

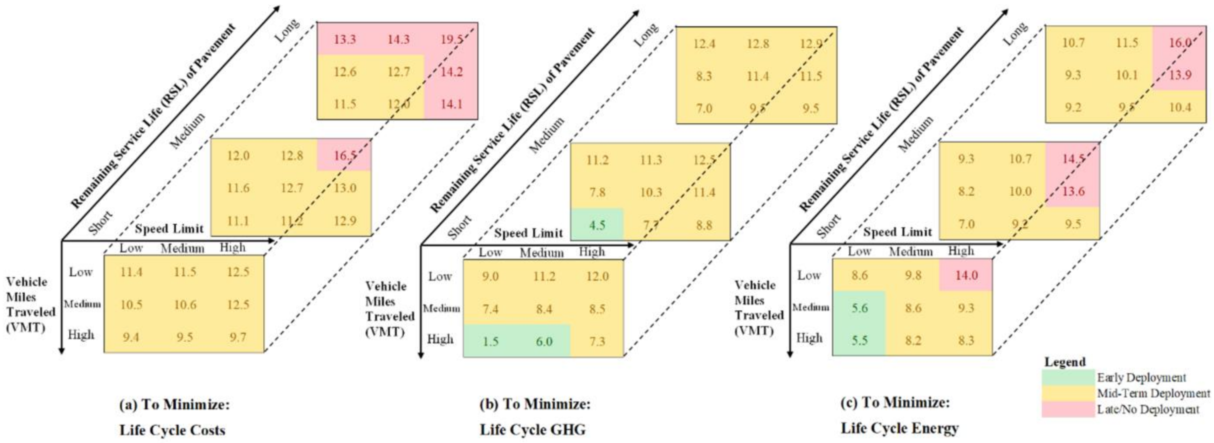


Figure 5.4 Recommended years to deploy DWPT on roadway segments based on the VMT, speed, and RSL of the segment for each objective of life cycle costs, GHG, or energy. The numbers in the figure indicate the average of deployment years for all segments in the respective categories. The three categories (low/short, medium, and high/long) of VMT, speed, and RSL of pavement are based on the 33% and 67% quantile statistics of the traffic counts data. The 33% and 67% quantiles for daily VMT are 12,746 and 48,322 vehicle miles traveled (equivalent to average daily volume of 6,971 and 26,429), for speed 55 and 70 miles per hour, and for RSL 3 and 6 years, respectively. The early, mid-term, and late/no deployment corresponds to 1-7 years, 7-13 years, and 13-20 years, respectively. GHG = greenhouse gas emissions; DWPT = dynamic wireless power transfer; VMT = vehicle miles traveled; RSL = remaining service life; and 1 mile ≈ 1.609 km.

Figure 5.5 shows the maps of optimal deployment of DWPT for objectives of minimizing life cycle costs, GHG, and energy. Generally, the deployment is later for the cost objective than for the GHG and energy objectives.

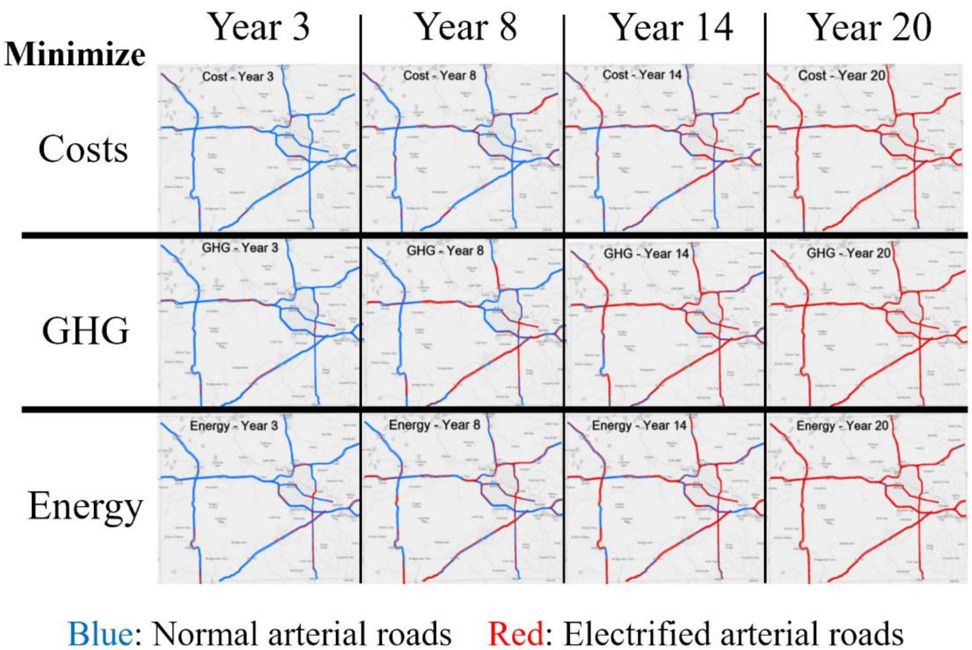


Figure 5.5 Optimal deployment of dynamic wireless charging infrastructure on arterial roads in Washtenaw County, Michigan, USA, with respect to each objective of minimizing life cycle costs, greenhouse gas (GHG) emissions, and energy burdens

5.4 Discussion

5.4.1 Breakeven and financial analyses

Return on investment. On one hand, the investment of DWPT infrastructure by transportation agencies is expensive and resource-intensive. On the other hand, there is societal payback from the revenues and emission and energy savings from the solar electricity charged when EVs are driving along DWPT-enabled roadways. Figure 5.6 shows the breakeven analysis of the life cycle costs, GHG, and energy burdens, using an example of the optimal deployment strategy for the scenario #6 at the minimized life cycle GHG emissions. The breakeven year or payback time is defined as the time required for the operational savings or revenues of charging EVs on DWPT lanes to repay the burdens of DWPT infrastructure. As shown in the base case, the net GHG and energy savings would break even at approximately year 19 and year 20, respectively, but the net profit of the money flow remains negative during the entire 20-year period. This finding of late cost breakeven time is consistent with a previous study that projected a cost breakeven in around 30 years [19]. Although the cost payback time is longer than 20 years, once paid back, the revenues generated from the operation of DWPT-EVs can be reinvested to expand the DWPT infrastructure to generate more revenues and GHG and energy savings. The sensitivity of infrastructure burdens is also illustrated. A 50% reduction of infrastructure burdens would accelerate the breakeven, shortening the breakeven period to about 13 years and 15 years in terms of GHG and energy, respectively. The profit of the money flow still remains negative though the breakeven is expected to be earlier than the base case. A 50% increase of infrastructure burdens would delay the breakeven longer than the 20-year period, regardless of cost, GHG, or energy.

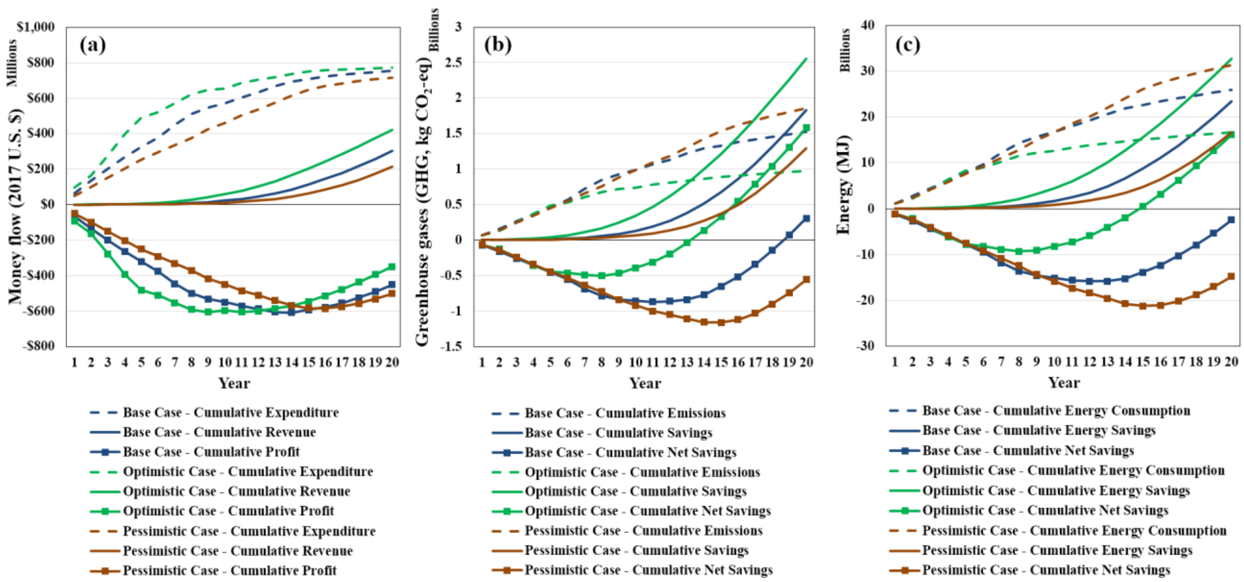


Figure 5.6 Breakeven analyses: (a) money flow; (b) greenhouse gases (GHG); and (c) energy. Compared to the base case, the optimistic case and the pessimistic case assume 50% and 150% of base infrastructure burdens (cost, GHG, or energy), respectively. The money flow is in 2017 present-value dollars

Sensitivity on annual budget constraint. To evaluate the effect of the annual budget constraint on the optimal DWPT deployment and coverage growth and EV market share increase, a sensitivity analysis is conducted using an example of scenario #6 at minimal life cycle GHG emissions, as shown in Figure 5.7. The annual budget in the base case is $30 million/year. On one hand, an annual budget lower than $15 million/year is found to significantly decelerate DWPT coverage and EV market share growth. On the other hand, an annual budget beyond $30 million/year would not significantly change the curves of DWPT coverage and EV market share growth, which means an annual budget of $30 million/year is already sufficient.

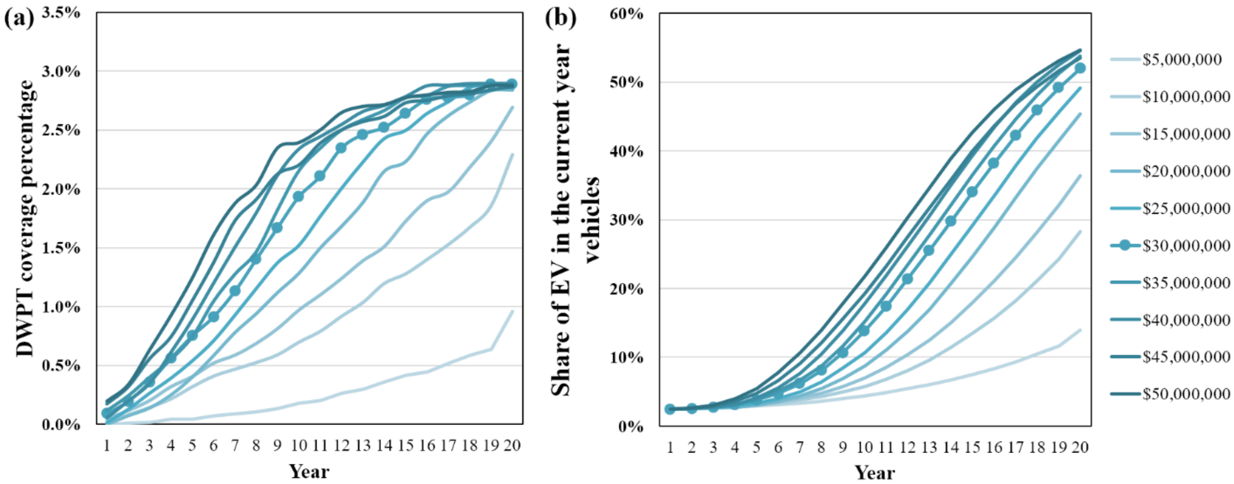


Figure 5.7 Sensitivity analysis of annual budget for deployment of dynamic wireless charging infrastructure. The annual budget in the base case is $30 million/year. Note: DWPT = dynamic wireless power transfer; and EV = electric vehicles

Social cost of carbon. In previous sections, the optimization problem in this study is solved separately for the objectives of life cycle costs and GHG emissions. Due to the high cost of DWPT deployment and the benefit of GHG savings in the use phase, the DWPT coverage growth at minimal life cycle costs is much slower than that at minimal life cycle GHG emissions. A social cost of carbon (SCC) [27] can be used to monetize the carbon emissions which would act as a policy to incentivize the DWPT deployment. Therefore, the two objectives of life cycle costs ($) and GHG emissions (kg CO_2-eq) can be unified in a single objective function with the same unit of U.S. dollar by using SCC ($/tonne of CO_2), as shown in Eq. 5.4, where *F* is the grand objective function ($), *LCC* is life cycle costs ($), *LCGHG* is life cycle GHG emissions (in tonne CO_2-eq), and *SCC* is social cost of carbon ($/tonne of CO_2). For simplification of the problem, SCC is assumed to monetize all GHG emissions (CO_2-eq), including carbon dioxide, methane, and nitrous oxide. As shown in Figure 5.8, with the increase of SCC from U.S. $50 to $1000 per metric tonne of CO_2, the DWPT deployment and EV market share curves are asymptotically close to the curves that minimize life cycle GHG emissions only. It is noteworthy that the carbon price required to transition from the “pro-cost” deployment to the “pro-GHG” deployment is at least $250 per metric tonne of CO_2 beyond which the deployment and EV market share curves start to lean towards GHG only curves. This “tipping-point” SCC is higher than the current level of SCC, which varies from $11 to $212 per metric tonne of CO_2 as estimated by an interagency study reported by the U.S. Environmental Protection Agency (EPA) [27]. This finding is consistent with the cost of

GHG mitigation of $556 per tonne of mitigated GHG reported in the Results Section. In order to reduce the GHG mitigation cost, it is recommended that future DWPT research and development should focus on the following aspects: (1) technical improvements to achieve a better wireless charging efficiency would help make the system more efficient thus more GHG can be mitigated per dollar of investment; (2) a better charging efficiency can also be achieved by the autonomous driving technology, which would help EVs keep aligned with DWPT energy supply units in the pavement and offset the deviation made by a human driver; (3) policy instruments, such as incentives and tax credits for wireless charging infrastructure and equipment, would lower the high investment costs.

$$F = LCC + LCGHG \times SCC \qquad \text{(Eq. 5.4)}$$

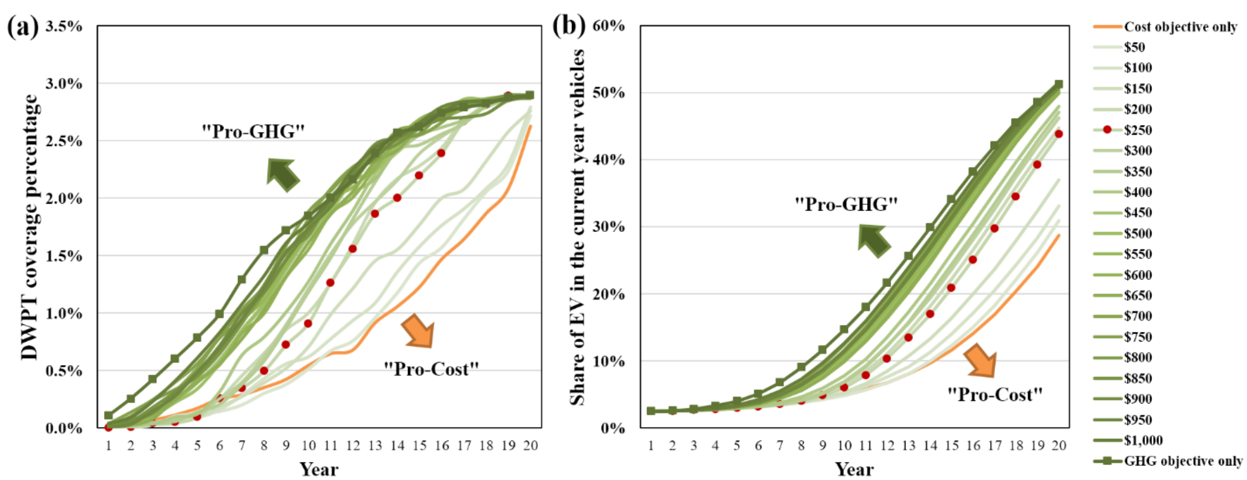


Figure 5.8 Effect of social cost of carbon (SCC) on the dynamic wireless charging infrastructure deployment and electric vehicle (EV) market share. The unit of SCC is U.S. dollars per metric tonne of CO_2. Note: DWPT = dynamic wireless power transfer; and GHG = greenhouse gases

5.4.2 Infrastructure improvements and management

Smart regulation to reduce congestion. DWPT performance can be enhanced by smart regulation of vehicle congestion. When EV market share is high but DWPT lanes are limited, there could be an imbalance of electricity supply and charging demand, resulting in traffic congestion on DWPT lanes. Both technology and economic mechanisms can be used to eliminate this concern so that it is sound to assume that if an EV cannot get the charge at a particular DWPT road segment due to congestion in the charging lane, then it can get equivalent charges elsewhere (e.g., on other

DWPT segments). For example, a smart regulation and intelligent vehicle-to-infrastructure communications can help find the best locations of DWPT lanes to charge the EVs based on their battery state of charge (SOC). EVs with lower SOC are given priority to charge first and EVs with higher SOC will charge later at other DWPT segments or SWPT stations. An electricity pricing mechanism that sets different prices of electricity charged to the EVs on different DWPT lanes based on the real-time congestion level can affect drivers' decisions on route choices so as to help regulate and decentralize congestion. Autonomous driving technology can also help maximize the utilization of DWPT by platooning, i.e., the gaps between EVs can be small, so that all EVs can still get the charge even if the market share of DWPT EVs is high.

Diversify DWPT charging power levels. In this study, 30 kW is assumed to be the power transfer level of DWPT. Technology improvement could increase the power rate level, e.g., to 60 kW. A high charging power is desirable for highways and a low power level would be sufficient for urban roads. The pros and cons of this diversification of power rate include: (1) Pro: a higher power rate would further reduce the range anxiety of EV customers and thus would boost the EV market share to a higher level [3]; (2) Pro: more electricity can be charged on a DWPT lane with higher power rate so that more revenue and GHG and energy benefits of clean solar electricity can be obtained, which accelerate the payback time; (3) Con: a higher power rate would require scaling up of infrastructure thus bringing additional infrastructure investment costs, which decelerate the payback time; and (4) Con: a higher power rate would also require more rigorous safety measures including electromagnetic shielding.

Asset management. The DWPT deployment can be coordinated with the normal scheduled pavement reconstruction, rehabilitation, and other repair work. Incentives should be given to encourage the concurrent DWPT deployment and road repair. Also, a proportional penalty of costs, GHG, or energy based on pavement burden should be applied if a good-condition pavement is torn up for DWPT deployment earlier than its service life.

End-of-life (EoL) management of DWPT infrastructure. A reusable and modular design of DWPT infrastructure embedded in pavement can help facilitate disassembly and recycling of metals and electronics. For example, although the proportion of life cycle GHG burdens from copper wires of wireless charging infrastructure is less than 1% based on the LCI results of this study, the metal after DWPT infrastructure retirement still has economic value. Therefore, recycling of reusable parts may offset some cost and environmental burdens of the initial infrastructure deployment and enhance the life cycle performance of DWPT. Given the uncertainty of which parts would be recycled after DWPT infrastructure retirement, the EoL stage is excluded in this LCA, but it is worth investigating the recycling benefits once sufficient data become available.

Electricity grid management. When there is no DWPT, EVs are typically charged overnight at home during the off-peak load of the electricity grid. However, when there is DWPT availability, some of the charging demand would be shifted from home at night to daytime. The additional load on the electricity grid from DWPT during daytime is both a challenge and an opportunity for enhancing the sustainability of wireless charging technology. On one hand, increase in charging demand would bring pressure on the electricity peak load because the traffic volume peak hours usually coincide with electricity peak load. On the other hand, the additional charging demand can be met by the clean renewable energy that is dispatched usually for marginal demand. In this case, the life cycle GHG and energy would be more accurately estimated using the marginal grid factors [28] characterizing marginal renewable energy than the average emission and energy intensity factors of all energy sources in the electricity grid, which can be an interesting topic to be explored in future work.

5.5 Conclusions

In this study, a life cycle assessment and optimization model is developed to evaluate and compare the life cycle costs, GHG emissions, and energy burdens of different deployment scenarios over a 20-year period, including the plug-in charging scenario, SWPT scenarios for charging at home/public parking and/or traffic lights, and DWPT scenarios with or without roadside solar electricity supply and with different regional electricity grid and fuel. The optimization of DWPT deployment encompasses two dimensions: (1) a spatial dimension, i.e., where to deploy DWPT, considering the VMT, speed, and RSL of each roadway segment; and (2) a temporal dimension, i.e., when to deploy DWPT, considering the EV market share boosted by DWPT and future cost reduction and efficiency improvement of DWPT. Based on a case study of arterial roads in Washtenaw County in Michigan, policy recommendations and optimal deployment strategies are provided.

Results indicate that compared to the non-DWPT scenarios, deployment of DWPT infrastructure has potential to reduce life cycle GHG emissions and energy by up to 9.0% and 6.8%, respectively, under either or both of the following conditions: (a) solar panels and storage batteries are present as electricity sources for EV charging; and (b) the regional electricity grid has low carbon and energy intensities, e.g., the California grid. However, deployment of DWPT infrastructure would not reduce life cycle costs, especially when solar panels and storage batteries are present as electricity sources for EV charging. Therefore, the larger-scale early and more aggressive deployment of DWPT is observed for GHG and energy objectives than for the cost objective, which triggers faster growth of EV market penetration. Electrification of up to about 3% of total roadway lane-miles in the region by deployment of DWPT would significantly help downsize the EV onboard battery capacity by 21% to 48% as compared to the battery capacity of 40 kWh for the plug-in charging scenario. Breakeven analysis indicates that a breakeven year for solar charging benefits to pay back the DWPT infrastructure burdens can be less than 20 years for GHG and energy burdens but longer than 20 years for costs. This finding of late cost breakeven time is consistent with a previous study that projected a cost breakeven in around 30 years [19]. Although life cycle costs of DWPT systems are high and the cost payback time is longer than the study period of 20 years, once paid back, the revenues generated from the operation of DWPT-EVs can be considerable. These can be reinvested to expand the DWPT infrastructure.

Based on the results, the following new insights about DWPT deployment are provided for decision making:

- If minimizing life cycle GHG or energy is prioritized as the main design objective, earlier deployment is generally preferable; if life cycle cost is prioritized, later deployment is desired. A monetization of carbon emissions of at least $250 per metric tonne of CO_2 is needed to shift the "pro-cost" deployment to the "pro-GHG" deployment.
- A roadway segment with high volume (greater than about 26,000 vehicle counts per day), low speed (slower than 55 miles per hour), and short RSL (shorter than 3 years) should be given a high priority for early-stage DWPT deployment.
- Solar panels and storage batteries are essential for significantly reducing life cycle GHG and energy burdens, so they are recommended to be deployed together with DWPT when

the design objective is prioritizing life cycle GHG emissions and energy burdens, with a precaution that they bring additional infrastructure costs.

- Deployment of DWPT in regions with a clean electricity grid, e.g., California, would yield more GHG and energy savings, so earlier and more aggressive deployment is preferred for states or regions with cleaner electricity than Michigan.

Technology innovations and smart regulation and management can help overcome the challenges and enhance the performance of DWPT. For example, autonomous driving technology can help guarantee the maximum possible charging efficiency by aligning the EVs with DWPT lanes perfectly. Smart regulation through vehicle to infrastructure (V2I) and vehicle to vehicle (V2V) technologies can also eliminate the concern of vehicle congestion on DWPT lanes. Diversification of DWPT charging power rate based on different roadway types, pavement asset management, and end-of-life management can also potentially enhance the life cycle performance of DWPT EV systems.

Appendix C Supporting information for Chapter 5

Life cycle inventory of dynamic wireless power transfer infrastructure

Introduction. A life cycle inventory (LCI) of dynamic wireless power transfer (DWPT) infrastructure for charging electric vehicles has been established and summarized. This section summarizes the LCI of infrastructure for dynamic wireless charging which encompasses the material production and infrastructure manufacturing life cycle stages.

Schematic. The diagram of the DWPT infrastructure is shown in Figure 5.9. The LCI encompasses the burdens from the electric grid power delivery infrastructure (feeder & connecting wires), WPT electronics (inverters, transformers, and coils), and roadway retrofitting (pavement).

Data sources. The LCI data of electronic components and other materials are based on the database available in SimaPro (e.g., EcoInvent, U.S. LCI, etc.). The DWPT power rate is 30 kW. The coil transmitter component is scaled up and adapted from the stationary wireless charger modeled in the authors' previous work [4] based on a 6 kW wireless charger developed by Professor Chris Mi's lab at the University of Michigan-Dearborn (now at San Diego State University). Other components of DWPT, including underground feeder, connecting wires, inverters, transformers, and pavement, are modeled as shown in Table 5.2.

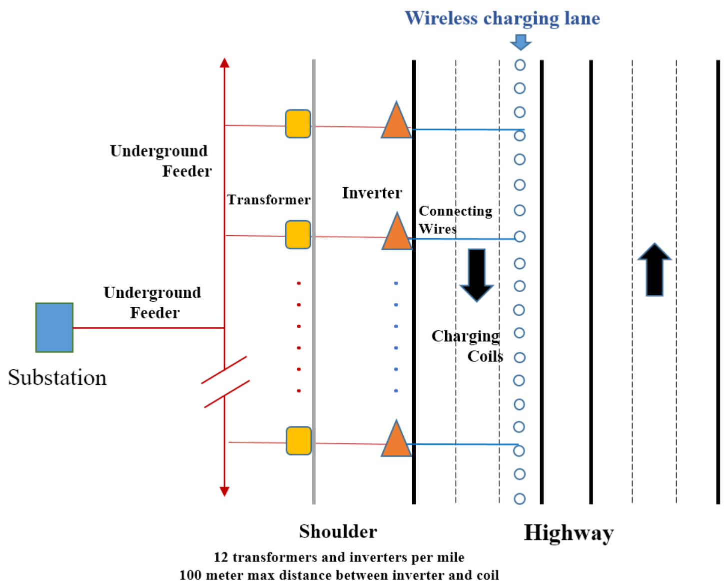


Figure 5.9 Schematic of dynamic wireless charging infrastructure. The figure is adapted based on a previous study [8].

Detailed components and their quantities per lane-mile of dynamic wireless charging infrastructure are summarized in Table 5.2. The element-wise burdens of each component are summarized in Table 5.3. Multiplying the values in Table 5.2 with those in Table 5.3 can obtain the total burdens of components per lane-mile. The system is designed such that the power rate capacity of the DWPT infrastructure would be sufficient to accommodate high penetration of electric vehicles traveling on the road at a high market share.

Table 5.2 Summary of components of dynamic wireless charging infrastructure per lane-mile

Component name	***Quantity per lane-mile***	***Unit***	***Source name in SimaPro***	***Note***
Underground feeder	1	mile	Transmission network, electricity, high voltage/CH/I U	25 kV
Connecting wires	1440	meters	Cable, three-conductor cable, at plant/GLO U	0.6 kV
Inverters	12	pieces	Inverter, 500kW, at plant/RER/I U	500 kW each
Transformers	12	pieces	Power, distribution, and specialty transformers	U.S. $5000 each
Coil transmitters	2476	pieces	Based on the previously modeled stationary wireless charger [4]	Scale up from 6 kW to 30 kW; Coil dimensions: 0.4 m × 0.3 m
Pavement	15973	kg	Bitumen, at refinery/kg/US	Asphalt volume per transmit coil (0.005376 m^3) × number of coils per lane-mile (2476) × asphalt density (1200 kg/m^3)

Note: 1 mile ≈ 1.609 km.

Table 5.3 Life cycle inventory burdens of key components

		Underground feeder	***Connecting wire***	***Inverter***	***Transformer***	***Coil transmitter***	***Pavement***
Basis for Inventory		mile	meter	piece	piece	6 kW piece	kg
Metric	*Unit*	*Value*					
CO_2-eq	kg	6.93E+04	2.50E+00	1.28E+04	6.06E+03	4.53E+02	5.43E-01
VOC	g	1.16E+02	3.21E-03	3.86E+01	1.39E+04	2.86E+00	1.22E-01
CO	g	7.58E+05	1.06E+01	4.72E+04	5.92E+04	8.57E+02	1.44E+01
NO_x	kg	1.35E+02	1.35E-02	2.66E+01	1.48E+01	1.17E+00	3.14E-03
PM10	mg	1.14E+08	1.04E+04	9.25E+06	3.23E+06	3.02E+05	7.22E+01
PM2.5	g	3.72E+04	5.62E+00	8.14E+03	1.86E+03	1.75E+02	0.00E+00
SO_x	kg	2.43E+02	5.63E-02	6.45E+01	1.33E+01	1.98E+00	4.64E-03
SO_2	kg	2.43E+02	5.63E-02	6.45E+01	1.33E+01	1.94E+00	1.79E-03
CH_4	g	1.35E+05	9.93E+00	2.31E+04	1.95E+04	7.62E+02	4.71E+00
CO_2	kg	6.01E+04	2.27E+00	1.24E+04	5.39E+03	4.28E+02	4.04E-01
CO_2 Biogenic	kg	9.90E+02	4.83E-02	2.37E+02	0.00E+00	1.13E+01	2.57E-03
N_2O	g	1.28E+03	1.27E-01	5.11E+02	1.58E+02	1.39E+01	2.73E-03
CF_4	mg	8.87E+05	6.40E-01	8.43E+03	0.00E+00	6.43E+02	0.00E+00
C_2F_6	mg	9.86E+04	7.16E-02	9.62E+02	0.00E+00	2.14E+02	0.00E+00
SF_6	mg	9.62E+02	6.64E-02	5.81E+02	0.00E+00	6.84E+02	0.00E+00
HFC-134a	mg	2.05E+03	6.99E-02	2.95E+02	0.00E+00	1.64E+01	0.00E+00
NO_2	g	0.00E+00	0.00E+00	0.00E+00	1.48E+04	1.60E+01	0.00E+00
Total Energy	MJ	1.08E+06	6.84E+01	2.31E+05	7.81E+04	7.62E+03	5.35E+01
Fossil Fuel	MJ	7.99E+05	5.69E+01	1.82E+05	7.81E+04	5.19E+03	5.35E+01
Crude Oil	MJ	0.00E+00	0.00E+00	0.00E+00	0.00E+00	1.96E+01	0.00E+00
Coal Fuel	MJ	0.00E+00	0.00E+00	0.00E+00	0.00E+00	2.50E+01	0.00E+00
Natural Gas Fuel	MJ	0.00E+00	0.00E+00	0.00E+00	0.00E+00	3.78E+01	0.00E+00
Water_Cooling	m^3	1.09E+03	5.35E-02	2.46E+02	0.00E+00	9.36E+00	0.00E+00

Note: 1 mile ≈ 1.609 km.

The fractional breakdown of LCI of dynamic wireless charging infrastructure per lane-mile is shown in Figure 5.10. And the detailed absolute values of life cycle inventory are summarized in Table 5.4.

Results indicate that coil transmitters dominate most of the metrics mainly due to the electronics, while transformers take up a large portion of VOC and NO_2. Note that this section summarizes the LCI of infrastructure for dynamic wireless charging, and not the use-phase electricity demand by electric vehicles and end-of-life impacts.

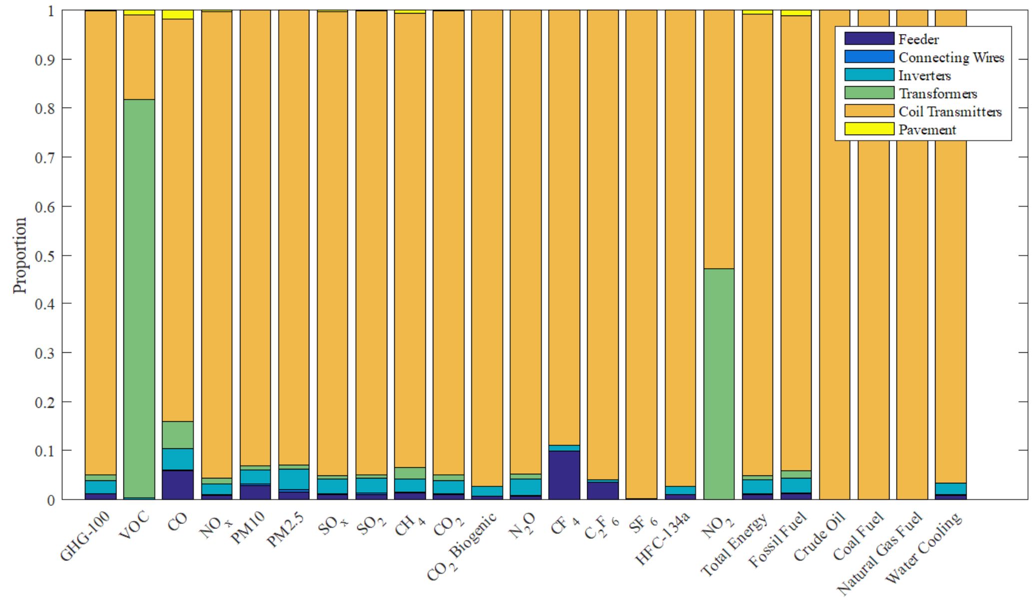


Figure 5.10 Fractional breakdown of life cycle inventory results of dynamic wireless charging infrastructure for different metrics

Table 5.4 Life cycle inventory of dynamic wireless charging infrastructure per lane-mile of roadway

Metric	*Unit*	*Feeder*	*Connecting wires*	*Inverters*	*Transformers*	*Coil transmitters*	*Pavement*	*Total*
GHG-100 (CO_2-eq)	kg	6.93E+04	3.60E+03	1.54E+05	7.27E+04	5.61E+06	8.67E+03	5.92E+06
VOC	g	1.16E+02	4.62E+00	4.63E+02	1.67E+05	3.54E+04	1.96E+03	2.05E+05
CO	g	7.58E+05	1.52E+04	5.66E+05	7.11E+05	1.06E+07	2.30E+05	1.29E+07
NO_x	kg	1.35E+02	1.94E+01	3.19E+02	1.77E+02	1.45E+04	5.02E+01	1.52E+04
PM10	mg	1.14E+08	1.49E+07	1.11E+08	3.87E+07	3.74E+09	1.15E+06	4.02E+09
PM2.5	g	3.72E+04	8.09E+03	9.77E+04	2.23E+04	2.17E+06	0.00E+00	2.33E+06
SO_x	kg	2.43E+02	8.11E+01	7.74E+02	1.60E+02	2.45E+04	7.42E+01	2.58E+04
SO_2	kg	2.43E+02	8.11E+01	7.74E+02	1.60E+02	2.40E+04	2.86E+01	2.53E+04
CH_4	g	1.35E+05	1.43E+04	2.77E+05	2.34E+05	9.43E+06	7.53E+04	1.02E+07
CO_2	kg	6.01E+04	3.27E+03	1.48E+05	6.47E+04	5.30E+06	6.45E+03	5.58E+06
CO_2 Biogenic	kg	9.90E+02	6.95E+01	2.84E+03	0.00E+00	1.40E+05	4.10E+01	1.44E+05
N_2O	g	1.28E+03	1.83E+02	6.14E+03	1.89E+03	1.72E+05	4.35E+01	1.81E+05
CF_4	mg	8.87E+05	9.21E+02	1.01E+05	0.00E+00	7.96E+06	0.00E+00	8.95E+06
C_2F_6	mg	9.86E+04	1.03E+02	1.15E+04	0.00E+00	2.65E+06	0.00E+00	2.76E+06
SF_6	mg	9.62E+02	9.56E+01	6.97E+03	0.00E+00	8.46E+06	0.00E+00	8.47E+06
HFC-134a	mg	2.05E+03	1.01E+02	3.54E+03	0.00E+00	2.03E+05	0.00E+00	2.09E+05
NO_2	g	0.00E+00	0.00E+00	0.00E+00	1.77E+05	1.97E+05	0.00E+00	3.75E+05
Total Energy	MJ	1.08E+06	9.85E+04	2.77E+06	9.37E+05	9.43E+07	8.55E+05	1.00E+08
Fossil Fuel	MJ	7.99E+05	8.19E+04	2.19E+06	9.37E+05	6.43E+07	8.55E+05	6.92E+07
Crude Oil	MJ	0.00E+00	0.00E+00	0.00E+00	0.00E+00	2.42E+05	0.00E+00	2.42E+05
Coal Fuel	MJ	0.00E+00	0.00E+00	0.00E+00	0.00E+00	3.09E+05	0.00E+00	3.09E+05
Natural Gas Fuel	MJ	0.00E+00	0.00E+00	0.00E+00	0.00E+00	4.68E+05	0.00E+00	4.68E+05
Water_Cooling	m^3	1.09E+03	7.70E+01	2.95E+03	0.00E+00	1.16E+05	0.00E+00	1.20E+05

Note: 1 mile ≈ 1.609 km.

Optimization model and parameters

Table 5.5 Definitions of variables and parameters

Symbol	*Definition*	Reference(s)
F	Objective function value of optimization (i.e., life cycle burden), which can be life cycle costs (U.S. \$), GHG (kg CO_2-eq), or energy (MJ) when conducting optimization for each objective	/
φ_s	A component of life cycle burden, as detailed in "Derivations", $s = 1, 2, ..., 11$	/
i	Year index, $i = 1, 2, ..., 20$, representing each year of the 20-year period	/
j	Road segment index, $j = 1, 2, ..., 154$, representing 154 segments of arterial roads in Washtenaw County, Michigan	/
k	Index for each hour of a day, $k = 1, 2, ..., 24$	/
θ_i	Annual expense (calculated) on DWPT deployment in a particular year i (U.S. \$)	/
c_i	Annual budget constraint (U.S. \$)	[12]
σ_s	Coefficients to convert quantities to life cycle burdens, $s = 1, 2, ..., 11$ for every life cycle component. Example: A coefficient in the unit of kg CO_2-eq/kWh is able to convert the quantity of use-phase electricity (kWh) to the life cycle burden in the unit of kg CO_2-eq. Please refer to "Derivations" for details.	[9, 29, 30]
x_{ij}	An element in the decision variable matrix $\boldsymbol{X}$, representing the DWPT deployment *status* of a road segment. If the segment j *is or has been* deployed with DWPT *in or before* year i, then $x_{ij} = 1$; otherwise $x_{ij} = 0$	/
x'_{ij}	An element in the matrix $\boldsymbol{X}'$ that is converted from the decision variable matrix $\boldsymbol{X}$. It represents the *action* of deployment of a road segment. If the segment j is deployed with DWPT *exactly* in year i, then $x_{ij} = 1$; otherwise $x_{ij} = 0$	/
x''_j	An element in the matrix $\boldsymbol{X}''$ that is converted from the decision variable matrix $\boldsymbol{X}$. It represents the year of deployment of DWPT for a road segment ($x''_j = 1, 2, 3, ..., 20$) or no deployment in any year ($x''_j = 0$)	/
l_j	The length of a road segment j (miles) measured on map	[31]
r_{ij}	Road repair indicator: If a road segment j is scheduled to be repaired in year i, then $r_{ij} = 1$; otherwise $r_{ij} = 0$	[10]
R_j	The year of scheduled road repair for road segment j	[10]
σ_{r_i}	Coefficient for road repair burden per lane-mile in a particular year	/
p_{ij}	Penalty term if a road segment is renovated for DWPT deployment earlier than the scheduled road repair	/
β_i	The burden (cost, GHG, or energy) of building one lane-mile of entire pavement in year i	[6]
ε_m	Proportion of annual maintenance burden relative to the DWPT deployment burden, which is assumed to be 2% ($\varepsilon_m = 0.02$)	/

L	Life of a component in the unit of miles. L_X where X can be: - L_{EV} = 160,000 miles (electric vehicle) - L_{onWC} = L_{EV} (on-board wireless charger) - L_{PC} = L_{EV} (plug-in charger) - L_{SWPTHP} = L_{EV} (SWPT at home/public parking) - L_{bat_i} modeled (fleet-average battery life in year i)	[24, 30]
Y	Life of a component in the unit of years. Y_X where X can be: - Y_{pavement} = 20 years (pavement) - Y_{DWPT} = 20 years (DWPT) - Y_{SWPTL} = 20 years (SWPT-Lights) - Y_{EV} = 11 years (electric vehicle) - Y_{solar} = 28 years (solar panels)	[6, 17, 32]
VMT_{EV_i}	Vehicle miles traveled in year i of all electric vehicles on the road segments	[5]
N_{int}	Number of traffic intersections electrified each year	/
l_{int}	Length of SWPT at each traffic intersection (all directions combined) (assumed to be 0.2 lane-miles per intersection)	/
$BatCap_{\mathrm{cum}_i}$	The weighted average of battery capacity of all EVs in operation in the current year i	/
$BatCap_i$	The average battery capacity of newly sold EVs in year i	/
E_{cell}	Life-time energy processed (kWh) per cell at 80% capacity threshold; E_{cell} = 34.342 kWh	[24]
α_i	Energy-processed per cell per year for a typical EV in year i	/
E_{demand_i}	Daily energy demand of a typical EV in year i	/
E_{charged_i}	Daily energy charged wirelessly of a typical EV in year i	/
ω	Window of state of charge (SOC), which is assumed to be 40% (ω = 0.40)	/
λ_{area}	Area (m^2) of solar panels per lane-mile	/
ψ	Maximum power demand (kW) for solar panels from EVs driving on the DWPT infrastructure per lane-mile	/
ϕ	Solar insolation flux: 4.2 kWh/m^2/day (Detroit, MI); 5.4 kWh/m^2/day (San Francisco, CA)	[33]
η_{module}	Solar module efficiency = 16%	[32]
π_{ij}	Replacement schedule of roadside battery for solar energy storage. If replaced at road segment j in year i , π_{ij} = 1; if replaced but the remaining years in the 20-year study period is less than the solar battery life, then $0 < \pi_{ij} < 1$ proportionally; otherwise π_{ij} = 0.	/
λ_{bcap}	Capacity of solar energy storage battery (kWh) per lane-mile	/
τ_{night}	Average number of hours without solar insolation, which is assumed to be 12 hours	/

μ	Adjustment factor for converting peak load charging demand to off-peak demand, which is assumed to be 0.25	/
η_{bat}	Battery charge/discharge efficiency = 90%	[4]
v_{ijk}	Vehicle miles traveled of EVs on road segment j during the k-th hour of the day (k = 1,2,…,24) in year i	[5]
$e_{\text{DW}_{ij}}$	Electricity charged wirelessly on DWPT per mile (kWh/mile)	/
$e_{\text{SWL}_{ij}}$	Electricity charged from SWPT at traffic light, which is allocated in one-mile of EV travel on the road segments (kWh/mile)	/
$e_{HP_{ij}}$	Electricity charged from SWPT at home/public parking, which is allocated in one-mile of EV travel on the road segments (kWh/mile)	/
$VMT_{\text{CV}_{ij}}$	Vehicle miles traveled of all conventional gasoline vehicles on road segment j in year i	[5]
ξ_i	Average fuel economy of conventional gasoline vehicles in year i (miles/gallon)	[17]

Note: 1 mile ≈ 1.609 km; GHG = greenhouse gases; DWPT = dynamic wireless power transfer; SWPT = stationary wireless power transfer; and EV = electric vehicle.

Objective function:

The objective function is the sum of life cycle burdens from different components, including DWPT and SWPT infrastructure, solar infrastructure, EV batteries, and use-phase energy consumption, etc., as specified in "Derivations".

$$F = \sum_{s=1}^{11} \varphi_s \qquad \text{(Eq. 5.5)}$$

Side note 1: The life cycle burden F can be life cycle cost, GHG, or energy burdens, depending on the objective currently under evaluation, by simply multiplying the corresponding coefficient σ_s to convert quantities to life cycle burdens.

Side note 2: For the life cycle cost analysis, a discount rate of 3% in nominal terms (or 0.5% in real terms) is applied to discount future costs back to the present value [34]. All costs are reported in present-value dollars.

Decision variables:

Binary decision variable matrix is defined as follows, indicating whether a roadway segment is a DWPT lane or not in a particular year.

$$\boldsymbol{X} = \left\{ x_{ij} \mid x_{ij} = 0, 1 \right\} \quad i = 1, 2, ..., 20; \; j = 1, 2, ..., 154 \quad \text{“Status”} \qquad \text{(Eq. 5.6)}$$

Side note 1: To facilitate calculation, $\boldsymbol{X}$ is also converted and equivalent to the following form to indicate the *action* of deployment in a particular year for each segment.

$$\boldsymbol{X}' = \left\{ x'_{ij} \mid x'_{ij} = 0, 1 \right\} \quad i = 1, 2, ..., 20; \; j = 1, 2, ..., 154 \quad \text{“Deploy”} \qquad \text{(Eq. 5.7)}$$

Side note 2: When coded in Matlab, $\boldsymbol{X}$ is in the following equivalent form, indicating the year of deployment of DWPT ($x''_j = 1, 2, 3, ..., 20$) or no deployment in any year ($x''_j = 0$):

$$\boldsymbol{X}'' = \left\{ x''_j \mid x''_j = 0, 1, 2, 3, ..., 20 \right\} \quad j = 1, 2, ..., 154 \qquad \text{(Eq. 5.8)}$$

Constraint:

The constraint limits the annual deployment of DWPT infrastructure within the annual budget. Eq. 5.10 determines the annual deployment costs of DWPT infrastructure by calculating the total costs of lane-miles of DWPT infrastructure deployed in a year ($\sum_{j=1}^{154} \sigma_{1_i} x'_{ij} l_j$) and considering the case that if the DWPT infrastructure is concurrently deployed along with the regular pavement construction work, then the pavement burdens ($\sum_{j=1}^{154} x'_{ij} r_{ij} l_j \sigma_{r_i}$) are credited.

$$\theta_i \le c_i \;\; \text{for} \;\; \forall i \in \{1, 2, ..., 20\} \qquad \text{(Eq. 5.9)}$$

$$\text{where} \;\; \theta_i = \sum_{j=1}^{154} (\sigma_{1_i} x'_{ij} l_j - x'_{ij} r_{ij} l_j \sigma_{r_i}) \qquad \text{(Eq. 5.10)}$$

Derivations:

The calculations of components of life cycle burdens are summarized below. In the equations, σ_s ($s = 1, 2, ..., 11$) represents the coefficients (e.g., kg CO_2-eq/kWh for component 10 electricity, s = 10) to convert quantities (e.g., kWh) to life cycle burdens (e.g., kg CO_2-eq) for each component (e.g., electricity), while σ_{r_i} ($i = 1, 2, ..., 20$) indicates the coefficient for road repair burden per lane-mile in a particular year i.

Component 1: Dynamic wireless power transfer (DWPT) - infrastructure

$$\varphi_1 = \sum_{i=1}^{20} \sum_{j=1}^{154} \left(\frac{20 - i + 1}{Y_{\text{DWPT}}} (\sigma_{1_i} x'_{ij} l_j - x'_{ij} r_{ij} l_j \sigma_{r_i}) + p_{ij} \right) \qquad \text{(Eq. 5.11)}$$

$$\text{where } p_{ij} = x'_{ij} \cdot \frac{\max\{R_j - i, 0\}}{Y_{\text{pavement}}} \cdot l_j \beta_i \qquad \text{(Eq. 5.12)}$$

Side note:

Life of a new pavement is assumed to be 20 years [6]. The burden is allocated to the rest of years in the 20-year study period by multiplying $\frac{20 - i + 1}{Y_{\text{DWPT}}}$.

The model assumes deployment of DWPT at the beginning of each year. The last deployment is at the beginning of the 20th year. All the deployment and operational burdens before and during the 20th year are counted, but the burdens during the 21st year and beyond are not counted.

The life of DWPT infrastructure is assumed to be 20 years. If DWPT is deployed at the beginning of the 1st year, then the full burden (costs, GHG, or energy) of DWPT infrastructure is counted in the life cycle analysis. But for the DWPT deployed after the 1st year, partial burden (costs, GHG, or energy) is counted. For example, if DWPT is deployed at the 11th year, only half of the original burden is counted because it can theoretically serve from the 11th to 30th year but we only count the 11th to 20th year in this study. For another example, if the DWPT is deployed at the beginning of the 20th year, then only 1/20 of the original DWPT infrastructure burden is counted.

Component 2: Dynamic wireless power transfer (DWPT) - maintenance

$$\varphi_2 = \sum_{i=1}^{20} \sum_{j=1}^{154} \sigma_{2_i} x_{ij} l_j \qquad \text{(Eq. 5.13)}$$

$$\text{where } \sigma_{2_i} = \sigma_{1_i} \varepsilon_{\text{m}} \qquad \text{(Eq. 5.14)}$$

Component 3: Onboard wireless chargers (on-WC)

$$\varphi_3 = \sum_{i=1}^{20} VMT_{\mathrm{EV}_i} \frac{\sigma_{3_i}}{L_{\mathrm{onWC}}} \quad \text{(Eq. 5.15)}$$

Component 4: Plug-in chargers (PC)

$$\varphi_4 = \sum_{i=1}^{20} VMT_{\mathrm{EV}_i} \frac{\sigma_{4_i}}{L_{\mathrm{PC}}} \quad \text{(Eq. 5.16)}$$

Component 5: Stationary wireless power transfer at home/public parking (SWPT-H/P)

$$\varphi_5 = \sum_{i=1}^{20} VMT_{\mathrm{EV}_i} \frac{\sigma_{5_i}}{L_{\mathrm{SWPTHP}}} \quad \text{(Eq. 5.17)}$$

Component 6: Stationary wireless power transfer at traffic lights (SWPT-Lights)

$$\varphi_6 = \sum_{i=1}^{20} \sigma_{6_i} N_{\mathrm{int}} l_{\mathrm{int}} \frac{20 - i + 1}{Y_{\mathrm{SWPTL}}} \quad \text{(Eq. 5.18)}$$

Component 7: Battery (electric vehicle)

$$\varphi_7 = \sum_{i=1}^{20} BatCap_{\mathrm{cum}_i} VMT_{\mathrm{EV}_i} \frac{\sigma_{7_i}}{L_{\mathrm{bat}_i}} \quad \text{(Eq. 5.19)}$$

$$\text{where } L_{\mathrm{bat}_i} = \frac{\min\{Y_{\mathrm{EV}}, \frac{E_{\mathrm{cell}}}{\alpha_i}\}}{Y_{\mathrm{EV}}} \cdot L_{\mathrm{EV}} \quad \text{(Eq. 5.20)}$$

Side note 1: $BatCap_i = \frac{E_{\mathrm{demand}_i} - E_{\mathrm{charged}_i}}{\omega}$ is converted to $BatCap_{\mathrm{cum}_i}$ by taking the weighted average of battery capacity of all EVs in operation in the current year. The electricity charged includes the dynamic charging and charging at traffic lights, which is calculated by multiplying charging efficiency, battery efficiency, power rate (30 kW) and the time spent on charging in the unit of hour.

Side note 2: The energy consumption rate (ECR) of EVs will decrease by 0.6% accordingly per 1% of vehicle weight reduction due to battery downsizing [35, 36]. This lightweighting correlation is used for calculating ECR (kWh/mile) of electric vehicles. For example, a 10% reduction in vehicle weight due to battery downsizing would reduce the ECR by 6%. The new ECR is obtained by multiplying the original ECR and (100% - ECR reduction percentage).

Component 8: Solar panels

$$\varphi_8 = \sum_{i=1}^{20}\sum_{j=1}^{154} \frac{20-i+1}{Y_{\text{solar}}} \sigma_{8_i} x'_{ij} l_j \lambda_{\text{area}} \quad \text{(Eq. 5.21)}$$

$$\text{where } \lambda_{\text{area}} = \frac{\psi}{\phi \eta_{\text{module}}} \quad \text{(Eq. 5.22)}$$

Component 9: Battery (solar)

$$\varphi_9 = \sum_{i=1}^{20}\sum_{j=1}^{154} \sigma_{9_i} \pi_{ij} l_j \lambda_{\text{bcap}} \quad \text{(Eq. 5.23)}$$

$$\text{where } \lambda_{\text{bcap}} = \frac{\psi \tau_{\text{night}} \mu}{\eta_{\text{bat}}} \quad \text{(Eq. 5.24)}$$

Eq. 5.24 estimates the capacity of solar energy storage battery (kWh) per lane-mile. The battery is used to charge electric vehicles when there is no solar insolation (e.g., nighttime), which is sized by considering the off-peak electricity demand and battery efficiency.

Component 10: Electricity

$$\varphi_{10} = \sum_{i=1}^{20}\sum_{j=1}^{154}\sum_{k=1}^{24} (\sigma_{10_{ik}} v_{ijk} (e_{\text{DW}_{ij}} + e_{\text{SWL}_{ij}} + e_{HP_{ij}})) \quad \text{(Eq. 5.25)}$$

Side note: Electricity charged from the electric grid in this model is calculated by multiplying power rate (30 kW) and the time spent on charging in the unit of hour.

Component 11: Gasoline

$$\varphi_{11} = \sum_{i=1}^{20}\sum_{j=1}^{154} \sigma_{11_i} \frac{VMT_{\text{CV}_{ij}}}{\xi_i} \quad \text{(Eq. 5.26)}$$

Other model details:

The learning curve of DWPT is shown in Figure 5.11. The future cost of DWPT is assumed to follow a learning curve with a learning rate of 20%, which means the cost of DWPT decreases by 20% for every doubling of cumulative production or deployment. It is assumed to be similar to the cost reduction of solar panels because their major components are electronics [20].

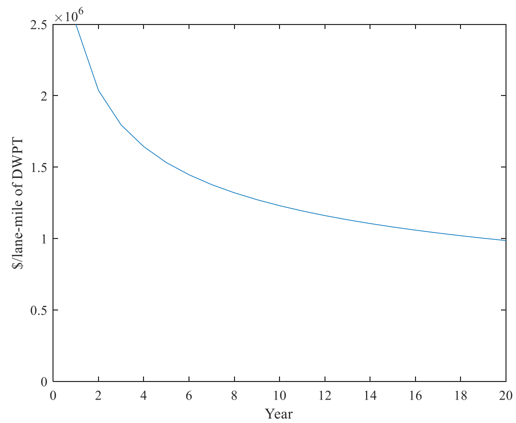


Figure 5.11 Learning curve of dynamic wireless power transfer (DWPT) infrastructure.

The extra EV sales boosted by increasing deployment of DWPT infrastructure compared to business-as-usual case is shown in Figure 5.12. The business-as-usual case assumes EV sales share increases from 2% in 2020 to 24% in 2050 [3]. The share of EVs in all vehicles currently in operation in a given year is calculated by taking the weighted average of past EV sales share within the last eleven years (= average vehicle life) [17].

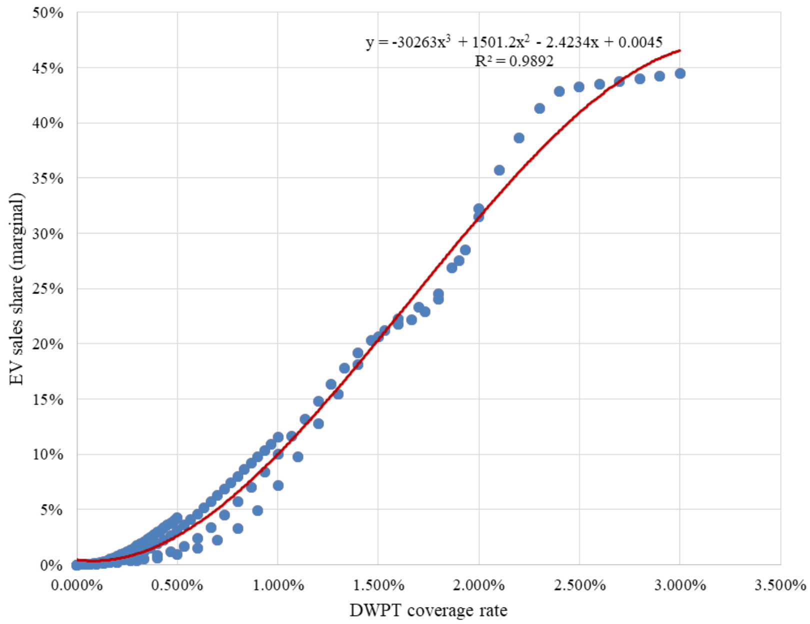


Figure 5.12 Extra sales share of electric vehicles (EV) boosted by increasing deployment of dynamic wireless power transfer (DWPT) infrastructure

Supplementary results

Temporal change in average energy consumption rate of all electric vehicles in operation is shown in Figure 5.13.

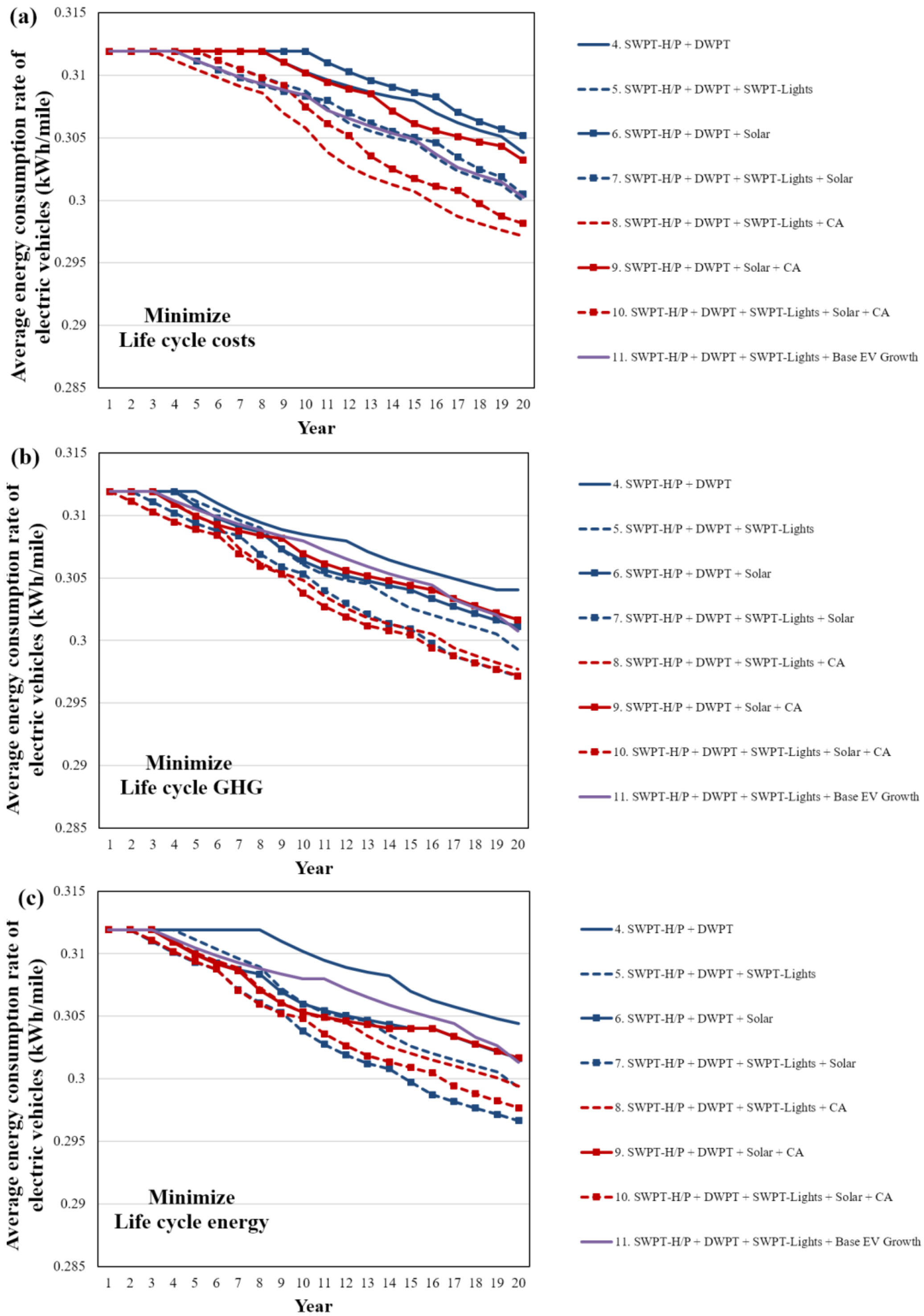


Figure 5.13 Temporal change in average energy consumption rate of all electric vehicles in operation. Note: GHG = greenhouse gases

Temporal change in theoretical battery life of all electric vehicles in operation is shown in Figure 5.14.

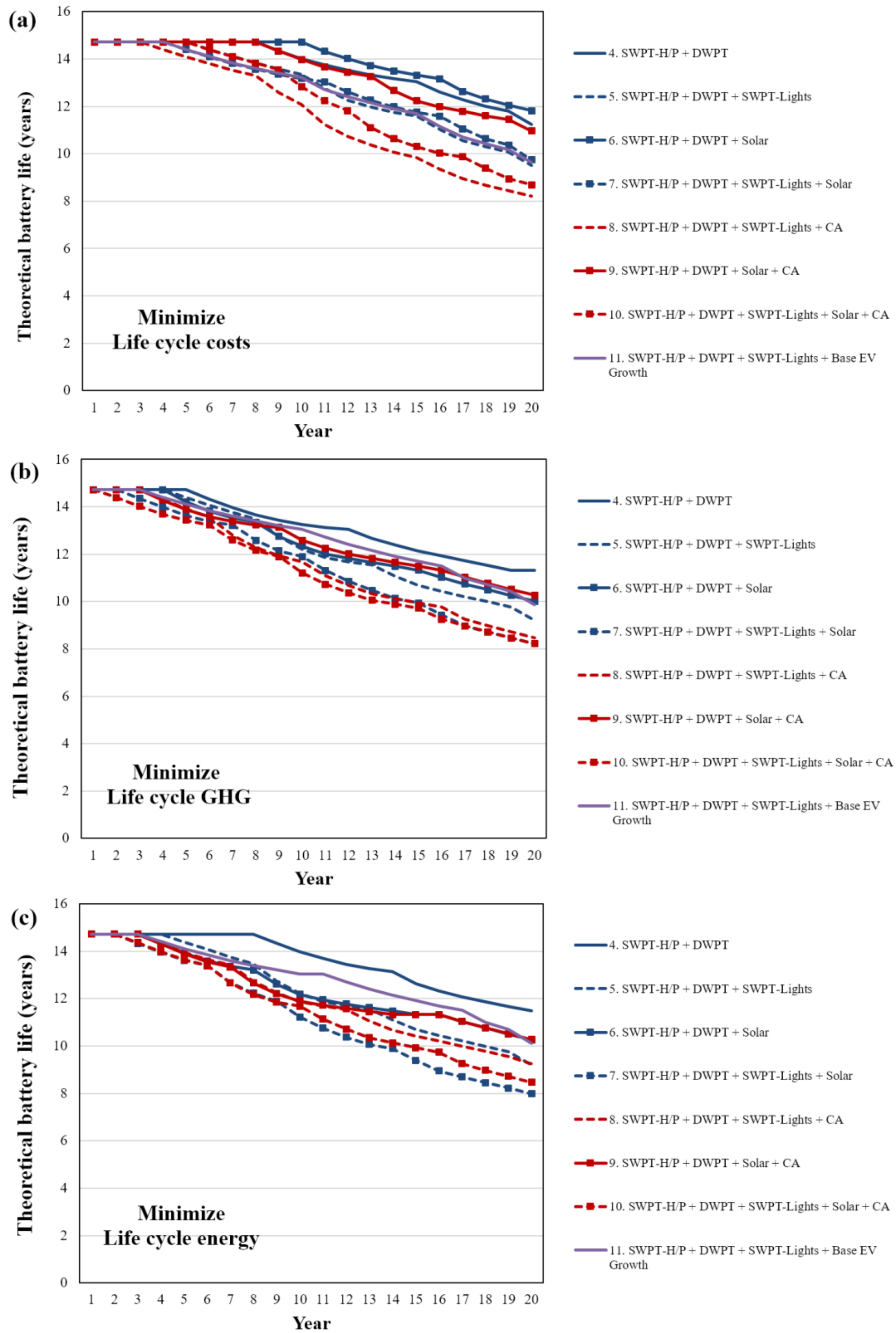


Figure 5.14 Temporal change in theoretical battery life of all electric vehicles in operation. Note: GHG = greenhouse gases

References

[1] Chen Z, He F, Yin Y. Optimal deployment of charging lanes for electric vehicles in transportation networks. Transport Res B 2016;91:344-65.

[2] Quinn JC, Limb BJ, Pantic Z, Barr P, Zane R. Techno-economic feasibly and environmental impact of wireless power transfer roadway electrification. In: 2015 IEEE wireless power transfer conference (WPTC). IEEE; 2015. p. 1-3.

[3] Lin Z, Li J, Dong J. Dynamic wireless power transfer: Potential impact on plug-in electric vehicle adoption. SAE Technical Paper 2014-01-1965; 2014.

[4] Bi Z, Song L, De Kleine R, Mi C, Keoleian GA. Plug-in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. Appl Energ 2015;146:11–9.

[5] MDOT. Traffic Monitoring Information System (TMIS) by Michigan Department of Transportation (MDOT), https://mdotnetpublic.state.mi.us/tmispublic/; 2017 [accessed June 2017].

[6] Zhang H. Sustainable pavement asset management based on life cycle models and optimization methods [Doctoral]. Ann Arbor, Michigan, USA: University of Michigan; 2009.

[7] Kim HC, Wallington TJ, Arsenault R, Bae C, Ahn S, Lee J. Cradle-to-gate emissions from a commercial electric vehicle Li-ion battery: A comparative analysis. Environ Sci Technol 2016;50(14):7715-22.

[8] Jones PT, Onar O. Impact of wireless power transfer in transportation: Future transportation enabler, or near term distraction. In: 2014 IEEE international electric vehicle conference (IEVC). IEEE; 2014. p. 1-7.

[9] U.S. EPA. Avoided emissions and generation tool (AVERT). U.S. Environmental Protection Agency (EPA) Office of Air and Radiation Climate Protection Partnerships Division; 2016.

[10] MDOT. Pavement management system by Michigan Department of Transportation (MDOT), https://mdotcf.state.mi.us/public/tms/index.cfm?see=pave; 2017 [accessed May 2017].

[11] MathWorks Inc. Genetic algorithm, https://www.mathworks.com/help/gads/genetic-algorithm.html; 2015 [accessed January 2017].

[12] Walter S at Michigan Department of Transportation (MDOT), Personal communication; October 4, 2017.

[13] Shahraki N, Cai H, Turkay M, Xu M. Optimal locations of electric public charging stations using real world vehicle travel patterns. Transport Res D 2015;41:165-76.

[14] Liu Z, Song Z. Robust planning of dynamic wireless charging infrastructure for battery electric buses. Transport Res C 2017;83:77-103.

[15] Hwang I, Jang YJ, Ko YD, Lee MS. System optimization for dynamic wireless charging electric vehicles operating in a multiple-route environment. IEEE Trans Intell Transp Syst 2017;PP(99):1-18.

[16] Ko YD, Jang YJ. The optimal system design of the online electric vehicle utilizing wireless power transmission technology. IEEE Trans Intell Transp Syst 2013;14(3):1255-65.

[17] U.S. DOT. National transportation statistics. Washington, D.C.: U.S. Department of Transportation (DOT) Bureau of Transportation Statistics; 2017.

[18] Bi Z, Kan T, Mi CC, Zhang Y, Zhao Z, Keoleian GA. A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility. Appl Energ 2016;179:413-25.

[19] Limb BJ. Optimization of roadway electrification integrating wireless power transfer: Technoeconomic assessment and lifecycle analysis [Master's]. Logan, Utah, USA: Utah State University; 2017.

[20] Rubin ES, Azevedo IML, Jaramillo P, Yeh S. A review of learning rates for electricity supply technologies. Energ Policy 2015;86:198-218.

[21] Bi Z, De Kleine R, Keoleian GA. Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system. J Ind Ecology 2016;21(2):344-55.

[22] Plugless Power. Plugless Power website, https://www.pluglesspower.com/; 2015 [accessed June 2015].

[23] U.S. EIA. Annual energy outlook 2012 with projections to 2035. Washington, D.C.: U.S. Energy Information Administration (EIA); 2012.

[24] Kelly J, Ersal T, Li C, Marshall B, Kundu S, Keoleian G, et al. Sustainability, resiliency, and grid stability of the coupled electricity and transportation infrastructures: Case for an integrated analysis. J Infrastruct Syst 2015;21(4):04015001.

[25] GasBuddy. Average gas prices by state, http://www.californiagasprices.com/Prices_Nationally.aspx; 2017 [accessed August 2017].

[26] U.S. EIA. Weekly retail gasoline and diesel prices, U.S. Energy Information Administration (EIA), https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_m.htm; 2017 [accessed August 2017].

[27] U.S. EPA. The social cost of carbon. Washington, DC: U.S. Environmental Protection Agency (EPA); 2017.

[28] Zivin JSG, Kotchen MJ, Mansur ET. Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. J Econ Behav Organ 2014;107:248-68.

[29] Goedkoop M, Oele M, Leijting J, Ponsioen T, Meijer E. Introduction to LCA with SimaPro. PRé Consultants; 2013.

[30] Argonne National Laboratory. The greenhouse gases, regulated emissions, and energy use in transportation (GREET) model, https://greet.es.anl.gov; 2017 [accessed May 2017].

[31] ArcGIS. ArcGIS online mapping tools, http://www.arcgis.com/features/index.html; 2017 [accessed May 2017].

[32] Stoppato A. Life cycle assessment of photovoltaic electricity generation. Energy 2008;33:224-32.

[33] National Renewable Energy Laboratory. The solar radiation data manual for flat-plate and concentrating collectors, http://rredc.nrel.gov/solar/old_data/nsrdb/1961-1990/redbook/; 2017 [accessed May 2017].

[34] OMB. Circular A-94 Appendix C (Revised November 2016) by the Office of Management and Budget (OMB) of the White House, https://obamawhitehouse.archives.gov/omb/circulars_a094/a94_appx-c; 2017 [accessed October 2017].

[35] Kim HC at Ford Motor Company, Personal communication; March 25, 2014.

[36] Kim HC, Wallington TJ. Life cycle assessment of vehicle lightweighting: A physics-based model of mass-induced fuel consumption. Environ Sci Technol 2013;47(24):14358-66.

CHAPTER 6

Enhancing sustainability of electrified mobility: Synergies of Wireless charging technology and Shared Autonomous Battery Electric Vehicles (W+SABEV)

Abstract

Emerging technologies play important roles in shaping future mobility systems and impacting their sustainability performance. This study applies a sustainability-based and life cycle framework to demonstrate and evaluate the synergies of the following four emerging technologies both qualitatively and quantitatively: (1) wireless charging technology; (2) shared mobility services technology; (3) autonomous driving technology; and (4) battery electric vehicle (BEV) technology. A wireless charging and shared autonomous battery electric vehicle (W+SABEV) system is modeled. First, a qualitative analysis assesses the pros and cons of the emerging W+SABEV system vs. the conventional plug-in charging BEV system, adhering to the principles of sustainable mobility, and highlights the impacts and dynamics of the disruptive technologies on the key parameters that define sustainable mobility. Second, a quantitative analysis presents the synergies of the four technologies by modeling a W+SABEV system and demonstrates that a conjunction of the four technologies can shorten the payback time of greenhouse gas (GHG) emission burdens in terms of infrastructure and vehicles. Policy recommendations are provided based on the results.

6.1 Introduction

A new era in transportation revolution is marked by recent dramatic transportation modal shifts, research and development (R&D) of clean vehicles and emerging technologies, and design of sustainable mobility systems. The trend is driven by three defining components: (a) a shared vehicle economy; (b) connected and automated vehicles (CAVs); and (c) vehicle electrification [1]. Each component offers a distinct set of benefits, poses a complex range of challenges, would fundamentally reshape vehicle and mobility systems, and ultimately enables a more sustainable means of moving people. To ensure a sustainable transition in transportation services, the diffusion of these three disruptive technologies requires a fundamental shift in our infrastructure in terms of the electric grid, road systems, and the way in which vehicles are fueled or charged [2].

Charging time, vehicle range, and availability of conventional plug-in charging infrastructure have long been cited as barriers to electric vehicle (EV) adoption [3]. Therefore, revolution of charging infrastructure and charging ways is a keystone in shaping future sustainable transportation and impacting EV adoption and performance of both private and public fleets. Recent breakthroughs in the field of wireless power transfer (WPT) have made the prospects of charging EVs wirelessly increasingly viable [3-7]. Without the use of wires, WPT describes the transfer of electricity across an electromagnetic field and uses magnetic resonance induction to transfer electricity from charging pads embedded within the ground to a pad installed on the vehicle. Under laboratory conditions, WPT can charge at an efficiency close to 90%, providing a similar charging power as the conventional plug-in method [3]. Compared to plug-in, wireless charging offers greater flexibility in its application, allowing vehicles to charge in stationary mode (i.e., when parked in garage or public parking spaces) or dynamic mode (i.e., in-route charging when vehicles are moving on roadways). Despite its current limited availability, many original equipment manufacturers (OEMs) of automobiles, such as Kia, BMW, Mercedes Benz, Nissan, Chevy, and Tesla, have already begun integrating wireless charging capability into EV design. Other companies, such as Plugless and Qualcomm, offer wireless charging pads that will be compatible with various vehicle models [3, 8].

Advances in wireless charging technology are perhaps the missing key to unlock the future of mobility systems. In addition to convenience and increased charging availability, WPT offers opportunities for downsizing the expensive and heavy EV onboard battery that enables vehicle lightweighting so as to improve EV fuel economy [9]. Despite a growing body of literature dedicated to R&D of each emerging technology respectively, little work explores the synergistic relationship between charging infrastructure and vehicle technologies in enhancing fleet performance and sustainable mobility, which poses a research gap as shown in Figure 6.1.

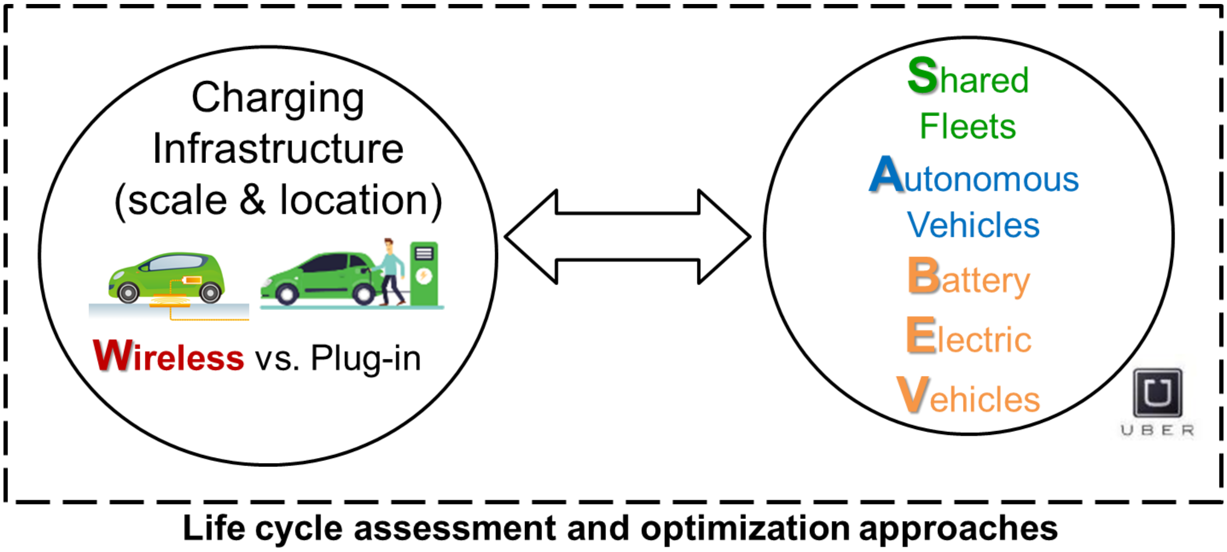


Figure 6.1 Research gap in evaluating charging infrastructure and vehicle technologies

The study in this chapter applies sustainability-based and life cycle framework to evaluate and demonstrate the synergies of the following four emerging technologies both qualitatively and quantitatively:

- Wireless charging technology
- Shared mobility services technology
- Autonomous driving technology
- Battery electric vehicle (BEV) technology

A wireless charging and shared autonomous battery electric vehicle (W+SABEV) system is modeled. First, a qualitative analysis assesses the pros and cons of the emerging W+SABEV system vs. the conventional plug-in charging BEV system, adhering to the principles of sustainable mobility, and highlights the impacts and dynamics of the disruptive technologies on the key parameters that define sustainable mobility. Second, a quantitative analysis presents the synergies of the four technologies by modeling a W+SABEV system and demonstrates that a conjunction of the four technologies can shorten the payback time of greenhouse gas (GHG) emission burdens in terms of infrastructure and vehicles.

6.2 Qualitative analysis

6.2.1 Method

A qualitative analysis is conducted based on a combination of literature review and assessment of vehicle technologies.

This study derives a life cycle-based framework to evaluate the sustainable mobility of proposed mobility systems based on the principles of green engineering [10]. We consider the in-use and upfront burdens for the cost, energy, and emissions of mobility systems, adopting a systems-level approach. Our framework serves as a general guideline to assess proposed mobility systems and technologies, highlighting notable trends that correspond to sustainable performance. Charging infrastructure utilization, vehicle utilization, and vehicle ownership are three trends that ultimately drive the sustainable performance of vehicle transportation [11].

The vehicle technologies and mode choices are predicted to shift dramatically [12]. A more in-depth summary of each mobility trend is provided as follows.

Shared mobility services. Market reports indicate that vehicle ownership will begin to decline [13, 14]. Shared vehicle fleets increase the utilization of a given vehicle, as private cars are estimated to be unused (parked) a majority of the time; the increase in vehicle utilization offers opportunities to enhance both sustainability and mobility [15]. Shared fleets can increase mobility for non-vehicle owners or populations no longer capable of driving. From a sustainability objective, the reduction of on-road vehicles in conjunction with their increased utilization will lead to significant reductions in emissions, energy demands, and system-wide costs. It is worth noting that shared mobility services should complement, not compete against, existing transportation systems. The prospect of shared fleets is promising, but the transition away from private vehicle ownership will be gradual and likely limited in non-urban environments.

Vehicle autonomy and connectivity. Connected and automated vehicles (CAV) technology allows for the real-time optimization of routes and charging decision-making. While only partial vehicle automation is currently commercially available, full scale driverless vehicles are predicted to hit the market within the next five to 20 years [16]. CAV technology enhances mobility through the optimization of traffic flow, demand forecasting, and increase in mobility for users that cannot drive, to name a few. From a sustainability perspective, CAV technology has the potential to reduce emissions through platooning, more efficient driving, and the optimization of charging time and location [3]. Research has also shown, however, that CAV technology may lead to an increase in VMT and decrease in vehicle fuel efficiency due to the increase in weight from the CAV technology [17]. Nonetheless, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication technologies allows for the data-drive, real-time operation of vehicles.

Powertrain technology. Currently, there are internal combustion engine vehicles (ICEVs), with hybrid electric (HEV), plug-in hybrid electric (PHEV), and battery electric vehicles (BEV) representing the remaining mix. Bloomberg New Energy Finance anticipates that EVs will constitute 55% of new sales and represent 33% of the global fleet by 2040 [18]. Battery electric vehicles offer the greatest opportunity to reduce greenhouse emissions, where a vehicle's relative impact is dependent on electricity grid emissions [19]. The emissions reduction between BEV and petroleum-based vehicle systems will only increase as renewable energy resources displace fossil fuel-based power generation.

Therefore, the shift towards shared mobility, vehicle autonomy, and electrified transportation are requisites for a future of sustainable mobility.

6.2.2 Results

6.2.2.1 Synergies of wireless charging and shared autonomous battery electric vehicles

Our qualitative analysis shows that charging infrastructure decision making requires that the synergies between vehicle technologies be explicitly considered. The advantages and disadvantages of each technology are summarized in Figure 6.2.

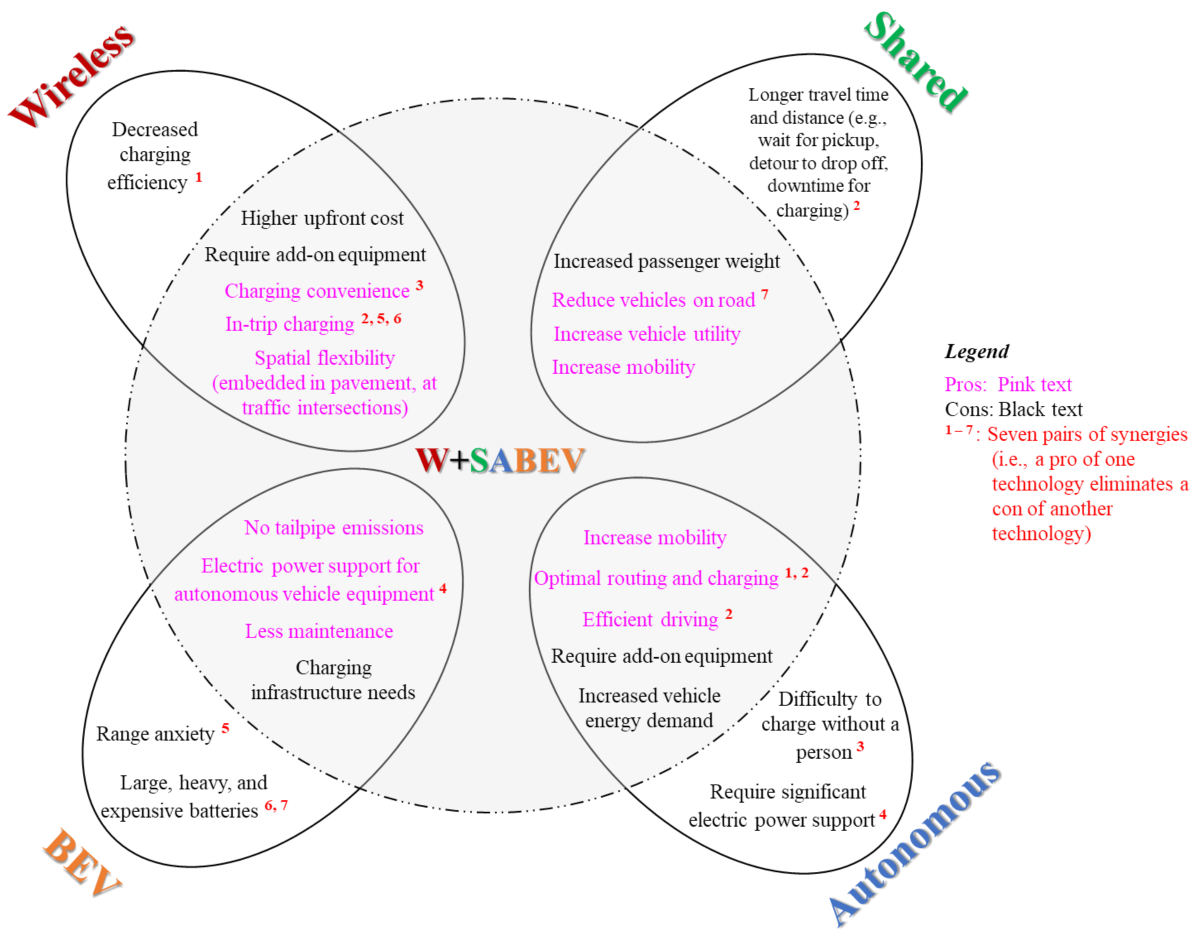


Figure 6.2 Advantages and disadvantages of vehicle technologies that distinguish synergies of a wireless charging and shared autonomous battery electric vehicle (W+SABEV) fleet

By integrating wireless charging technology instead of the conventional plug-in charging technology to charge electric vehicles, the pros of each technology can be enhanced, and some of cons of each technology can be eliminated. The key synergies are summarized as follows.

Synergies between wireless charging and shared mobility services technologies. On-road wireless charging can extend the operation time of shared fleets by recharging the battery incrementally, reducing the time and distance a vehicle must dedicate to maintain a minimum battery range. The spatial flexibility wireless charging provides aligns with the dynamic operations that shared fleets offer, highlighting the larger shift away from centralized vehicle infrastructure. Despite limited research that models shared autonomous fleets with respect to various charging scenarios, initial research indicates that wireless charging reduces both labor costs and nonpassenger vehicle miles traveled (VMT), making shared, electric fleets financially competitive compared to shared internal combustion engine (ICE) fleets [2].

Synergies between wireless charging and autonomous driving technologies. The benefits of both technologies are realized when deployed in conjunction. Wireless charging supports the full automation of vehicles as they can charge without the need of human intervention. Wireless charging also allows autonomous vehicles to strategically charge not only in parked spaces, but also at traffic lights and along the road when dynamic charging is considered. Vehicle autonomy is needed to realize the benefits of wireless charging for a variety of reasons. From a technical standpoint, an autonomous vehicle will maximize the charging efficiency by perfectly aligning the wireless charging pads. An autonomous vehicle offers communication between both vehicles and infrastructure. It can select optimal times and locations for charging by smart routing. An autonomous vehicle can also park itself and charge itself without any human intervention, reducing the amount of charging stations needed when vehicles are not in use. Research on SABEV systems has concluded that wireless charging increases operational efficiency, as vehicles can incrementally charge themselves throughout service [1, 2].

Synergies between wireless charging and BEV technologies. Although the large-scale wireless charging infrastructure poses significant deployment burdens, it offers opportunities to downsize the expensive and heavy BEV battery by recharging it incrementally to still satisfy the desired vehicle range. Such trade-offs are most evident when modeling the relationship between vehicle battery size and charging station placement. With respect to fixed bus routes, my previous study has shown that wireless charging for buses allows batteries to be 27% – 44% the size of a plug-in charged battery. This battery downsizing would result in lightweighting the vehicle and improving the fuel economy [9]. Wireless charging also offers spatial flexibility for charging infrastructure deployment, because it can be built on existing roads or parking spaces, without the need of procuring new lots to build plug-in charging stations. This would address the challenges of spatially constrained cities to supply adequate charging infrastructure.

6.2.2.2 System dynamics and key parameters for sustainability

Having shown the potential of wireless charging technology to enhance the sustainable mobility of SABEV systems, this study shifts the focus to the dynamics of critical parameters, trade-offs, and constraints which define such systems. The system dynamics driven by the disruptive technologies are shown in Figure 6.3. It is assumed that the system seeks to serve a fixed passenger travel demand in a given day. By penetrating the disruptive technologies into the system, there will be changes driven by that penetration, as highlighted in the figure. The results are a combination of both positive and negative feedbacks demonstrating the interconnected complexity of passenger travel demand, vehicle design, and infrastructure needs. Wireless charging can: ① reduce the battery capacity due to more in-route charging time and charger utility improvement by optimal siting of charging infrastructure; ② reduce range anxiety due to more charging availability, therefore stimulating EV market share growth [20]. As such, wireless charging serves as the necessary catalyst to spark adoption trends and improve sustainable mobility; and ③ increase the production burden and weight of vehicles due to the add-on equipment of onboard wireless charger. Shared mobility can increase the ridership which results in extra distance detoured to pick up and drop off the additional passengers and add-on vehicle weight from the additional passengers, but it would reduce the fleet size required to serve the same amount of passenger travel. Autonomous driving technology would: ① reduce trip distance and improve fuel economy by smart routing; ② improve vehicle range and service time because of continuous operation of driverless vehicles as compared to a human-driving vehicle operation that may be interrupted by the driver's need to rest after a few hours of driving; ③ improve the wireless charging efficiency by aligning the onboard charging pads perfectly with the off-board charging pads by precisely detecting the location of the wireless charging transmitter coils on the ground; ④ increase the production burdens, weight, and air drag of the vehicles due to the add-on equipment of autonomous technology (e.g., lidar and computing systems); and ⑤ reduce the vehicle weight due to no need of driver.

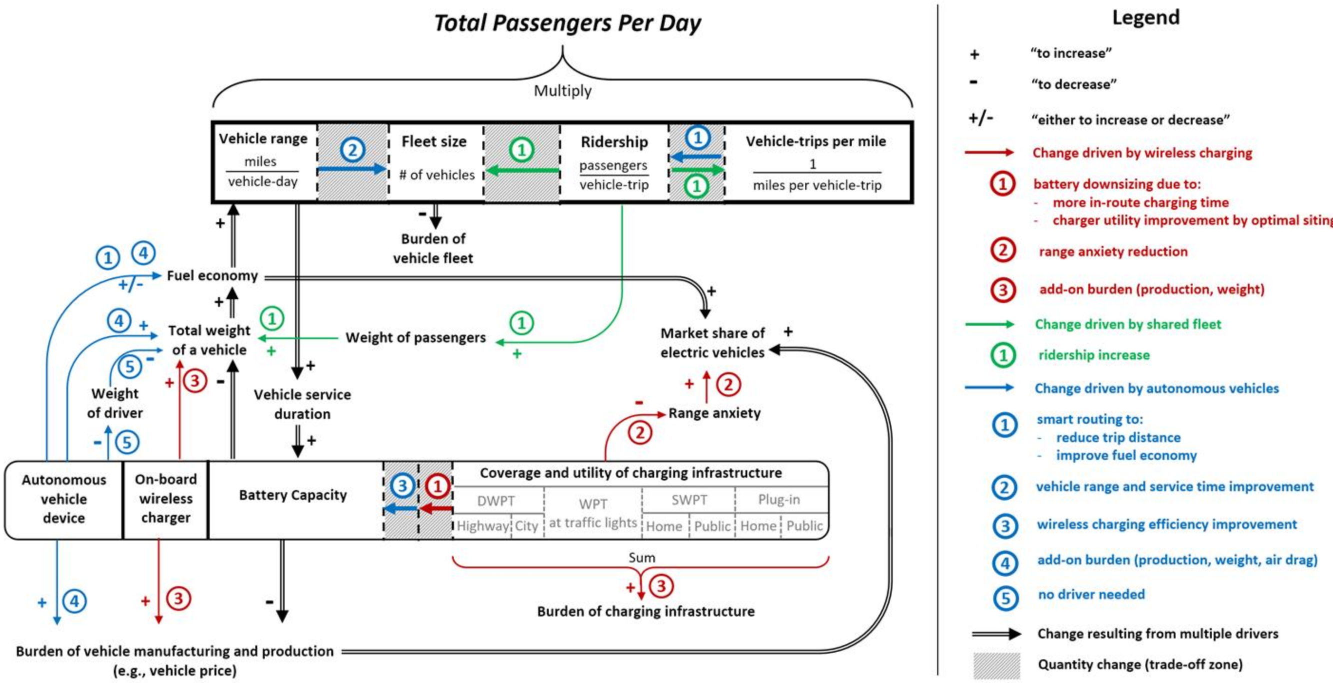


Figure 6.3 System dynamics driven by the disruptive technologies

6.3 Quantitative analysis

6.3.1 Method

A life cycle model is developed to evaluate the synergistic effect of the four emerging technologies on the payback time of greenhouse gas (GHG) emissions of infrastructure and vehicle burdens, by comparing a W+SABEV system (System #1) vs. a plug-in charging BEV system (System #2) serving the same number of 12,500 passengers on a daily basis.

The GHG payback time is defined as the time when the additional burdens resulting from System #1 is equal to the cumulative savings of System #1, as compared to System #2. The additional burdens include: (1) wireless charging infrastructure; (2) additional weight of passengers; and (3) autonomous vehicle device. The additional savings include: (1) fleet size reduction; (2) battery downsizing; (3) no driver weight; and (4) use-phase electricity savings. The emission factors of these burdens and savings are obtained from the literature [9, 17, 21, 22].

Key parameters of System #1 are varied to illustrate their impacts on the GHG payback time, number of vehicles needed and average battery capacity of EVs, as shown in Table 6.1. The variation range of each key parameter is based on empirical estimate. Wireless charging utility factor is defined as the average percentage of time that a W+SABEV spends on charging relative to the entire trip duration, namely the probability that a W+SABEV encounters an available charging facility in route. Smart routing factor is defined as the ratio of the trip distance after and before autonomous driving technology is employed.

Table 6.1 Model setup for system comparison

Key parameters	**System #1** **W+SABEV**	**System #2** **Plug-in Charging BEV**
Wireless charging utility factor	5% – 25%	N/A
Average ridership per EV	1.5 passengers – 2.25 passengers	1.5 passengers
DWPT efficiency	65% – 80%	N/A
Vehicle range per EV per day	120 miles – 180 miles	120 miles
Smart routing factor	1.00 – 0.85	1.00

6.3.2 Results

The impacts on GHG payback time, fleet size, and average battery capacity from individual technology as well as all technologies in conjunction are shown in Figure 6.4. The results indicate that deploying all of those technologies in conjunction would significantly decrease the GHG payback time, number of vehicles, and battery capacity. Individual technology alone would not achieve such a great reduction.

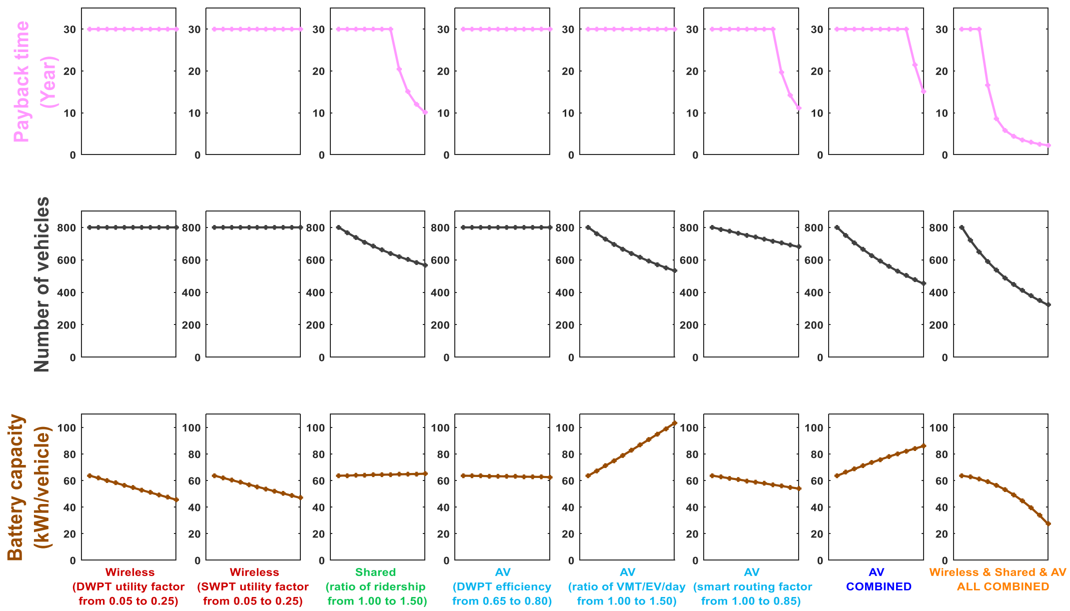


Figure 6.4 Effect of each technology on the payback time, fleet size, and battery capacity

Further analysis demonstrating the impact of wireless charging utility factor on the GHG payback time by evaluating an average W+SABEV fleet, as shown in Figure 6.5. Compared to a plug-in charging BEV system, a W+SABEV system with wireless charging utility factor <= 5% will pay back GHG emission burdens of additional infrastructure deployment beyond 10 years; and a W+SABEV system with wireless charging utility factor >= 19% will pay back GHG emission burdens of additional infrastructure deployment within 5 years. The presented sustainability framework suggests that a high utilization of a given system is a fundamental requisite for its overall sustainability. Within the context of transportation systems, this implies that vehicle operation time and range should be maximized and charging infrastructure should be fully utilized through optimal deployment. This principle of utility maximization is essential so that the upfront burdens can be offset by in-use savings.

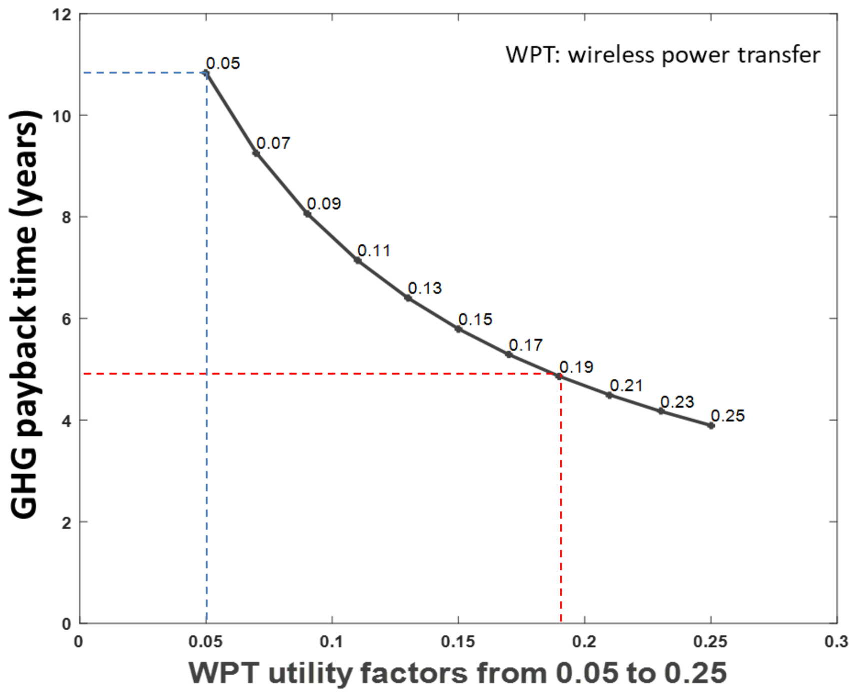


Figure 6.5 Effect of wireless charging utility factor on the payback time

6.4 Conclusions

The current body of literature focuses on the analysis of interactions between transportation systems and emerging technologies. While it is vital to develop each emerging technology and improve its individual performance, it is equally important to recognize and assess the synergistic effects of the following emerging technologies and the interconnection between vehicle and infrastructure:

- Wireless charging technology
- Shared mobility services technology
- Autonomous driving technology
- Battery electric vehicle technology

Through both qualitative and quantitative analyses and a parametric model of a W+SABEV fleet, the synergistic effects of the four technologies are demonstrated in enhancing sustainability of future transportation and reducing payback of upfront GHG emission burdens from infrastructure and vehicles. Results indicate that based on the status quo of technology development using 2018 data, compared to a plug-in charging BEV system:

- A W+SABEV system with wireless charging utility factor <= 5% will pay back GHG emission burdens of additional infrastructure deployment beyond 10 years;
- A W+SABEV system with wireless charging utility factor >= 19% will pay back GHG emission burdens of additional infrastructure deployment within 5 years.

References

[1] Fagnant DJ, Kockelman KM. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transport Res C 2014;40:1-13.

[2] Chen TD, Kockelman KM, Hanna JP. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. Transport Res A 2016;94:243-54.

[3] Bi Z, Kan T, Mi CC, Zhang Y, Zhao Z, Keoleian GA. A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility. Appl Energ 2016;179:413-25.

[4] Kan T, Nguyen T-D, White JC, Malhan RK, Mi C. A new integration method for an electric vehicle wireless charging system using LCC compensation topology: Analysis and design. IEEE Trans Power Electron 2016;PP(99):1-12.

[5] Liu Z, Song Z. Robust planning of dynamic wireless charging infrastructure for battery electric buses. Transport Res C 2017;83:77-103.

[6] Li S, Mi C. Wireless power transfer for electric vehicle applications. IEEE J Emerg Sel Topics Power Electron 2014;3(1):4-17.

[7] Lee S, Choi B, Rim CT. Dynamics characterization of the inductive power transfer system for online electric vehicles by Laplace phasor transform. IEEE Trans Power Electron 2013;28(12):5902-9.

[8] Plugless Power. Plugless Power website, https://www.pluglesspower.com/; 2015 [accessed June 2015].

[9] Bi Z, Song L, De Kleine R, Mi C, Keoleian GA. Plug-in vs. wireless charging: Life cycle energy and greenhouse gas emissions for an electric bus system. Appl Energ 2015;146:11–9.

[10] Anastas PT, Zimmerman JB. Design through the 12 principles of green engineering. Environ Sci Technol 2003;37(5):94A-101A.

[11] Sperling D. Three revolutions: Steering automated, shared, and electric vehicles to a better future: Island Press; 2018.

[12] Fulton L, Mason J, Meroux D. Three revolutions in urban transportation: How to achieve the full potential of vehicle electrification, automation, and shared mobility in urban transportation systems around the world by 2050. No. STEPS-2050; 2017.

[13] Arbib J, Seba T. Rethinking transportation 2020-2030. RethinkX; 2017.

[14] Johnson C, Walker J. Peak car ownership: The market opportunity of electric automated mobility services. Rocky Mountain Institute; 2016.

[15] Shoup D. The high cost of free parking: Updated edition: Routledge; 2017.

[16] Anderson JM, Nidhi K, Stanley KD, Sorensen P, Samaras C, Oluwatola OA. Autonomous vehicle technology: A guide for policymakers: Rand Corporation; 2014.

[17] Gawron JH, Keoleian GA, De Kleine RD, Wallington TJ, Kim HC. Life cycle assessment of connected and automated vehicles: Sensing and computing subsystem and vehicle level effects. Environ Sci Technol 2018;52(5):3249-56.

[18] BloombergNEF. Electric vehicle outlook 2018. Bloomberg New Energy Finance (NEF); 2018.

[19] Zivin JSG, Kotchen MJ, Mansur ET. Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. J Econ Behav Organ 2014;107:248-68.

[20] Lin Z, Li J, Dong J. Dynamic wireless power transfer: Potential impact on plug-in electric vehicle adoption. SAE Technical Paper 2014-01-1965; 2014.

[21] Kim HC, Wallington TJ, Arsenault R, Bae C, Ahn S, Lee J. Cradle-to-gate emissions from a commercial electric vehicle Li-ion battery: A comparative analysis. Environ Sci Technol 2016;50(14):7715-22.

[22] Argonne National Laboratory. The greenhouse gases, regulated emissions, and energy use in transportation (GREET) model, https://greet.es.anl.gov; 2017 [accessed May 2017].

CHAPTER 7
Conclusions

The economic, environmental, and energy performance of wireless charging technology in enhancing sustainable mobility is evaluated by developing an integrated LCA-LCC model framework and optimized through LCO techniques on siting or rolling out wireless charging infrastructure.

The LCA-LCC and LCO model framework is applied to evaluate the following transportation systems: (1) transit bus systems (Chapters 3 and 4); (2) passenger car systems (Chapter 5); and (3) a shared automated battery electric vehicle system (Chapter 6). The developed LCA-LCC and LCO framework lays a foundation for future work to evaluate and optimize similar emerging technologies for sustainable transportation.

Overall, wireless charging is applicable to stationary wireless charging transit bus systems and can achieve comparable life cycle costs, greenhouse gases (GHG), and energy vs. plug-in charging systems. Optimal siting of wireless charging bus stations would enhance performance and reduce life cycle costs, GHG, and energy by up to 13%, 8%, and 8%, respectively. Deployment of dynamic wireless charging infrastructure for passenger cars is much more challenging and requires alignment of the following to enhance environmental, energy, and economic performance: (1) strategies considering both spatial and temporal heterogeneity are needed for optimal deployment, including high traffic volume, low speed, poor pavement conditions, high charging efficiency, and low infrastructure costs; (2) clean electricity sources such as solar energy; and (3) high penetration of electric vehicles in the market. A case study of Washtenaw County indicates that optimal deployment of DWPT electrifying up to about 3% of total roadway lane-miles reduces life cycle GHG emissions and energy by up to 9.0% and 6.8%, respectively, and enables downsizing of the EV battery capacity by up to 48% compared to the non-DWPT scenarios and boosts EV market penetration to around 50% of all vehicles.

It is also highlighted that wireless charging technology has strong synergies with autonomous driving technology. The application of wireless charging technology in a shared automated battery electric vehicle system is promising in significantly reducing GHG payback time of charging infrastructure.

The detailed conclusions from each section are summarized in the following sections.

7.1 Opportunities and challenges for wireless charging technology to enhance sustainable mobility (Chapter 2)

From the sustainability perspective, WPT EVs have the trade-off of large infrastructure deployment versus the benefits of battery downsizing and vehicle lightweighting. WPT technology offers the possibilities for better energy performance, lower environmental impacts, lower life cycle cost, and more convenience and operational safety benefits compared to wired EVs and conventional internal combustion engine vehicles (ICEVs).

In order to realize these possibilities of WPT EVs, the following research gaps need to be filled:

- Optimization of large scale charging infrastructure deployment and battery capacity with a consideration of battery life for both public transit and passenger car applications;
- Policies that coordinate the growth and development of WPT technology with other emerging EV technologies, such as connected and automated vehicles (CAVs); and
- Electricity grid management that balances the demand and supply of electricity for both static and moving vehicles.

Connected and automated vehicles (CAVs) would provide strong synergy and accelerate the adoption of WPT technology by leveraging capabilities (such as charging alignment precision) to improve driving performance and energy efficiency. WPT technology also offers more connectivity with the electric grid through V2G and G2V bidirectional power transfer, enabling EVs to become mobile energy storage devices to help regulate the grid by storing excess generation from uncontrolled renewables.

7.2 Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system (Chapter 3)

A case study of Ann Arbor transit bus systems indicates that despite a higher initial infrastructure investment for off-board wireless chargers deployed across the service region, the wireless charging bus system has the lowest LCC of US$0.99 per bus-kilometer compared to plug-in charging and also conventional pure diesel and hybrid bus systems and has the potential to reduce use-phase carbon emissions attributable to the lightweighting benefits of on-board battery downsizing compared to plug-in charging.

7.3 A multi-objective life cycle optimization model of wireless charger deployment for an electric bus network (Chapter 4)

There is no significant conflict among the cost, GHG, and energy objectives so that a near-optimal deployment of wireless charging stations can achieve all three objectives almost simultaneously. For example, when planners optimally site the charging stations for the purpose of minimizing life cycle costs, they would almost achieve the minimal life cycle GHG emissions and energy consumption as well.

Based on the case study of the University of Michigan bus routes, the optimal siting strategies can help reduce life cycle costs, GHG, and energy by up to 13%, 8%, and 8%, respectively, compared to extreme cases of "no charger at any bus stop" and "chargers at every stop".

7.4 Life cycle assessment and tempo-spatial optimization of deploying dynamic wireless charging technology for electric cars (Chapter 5)

In this study, a life cycle assessment and optimization model was developed to evaluate and compare the life cycle costs, GHG emissions, and energy burdens of different deployment scenarios over a 20-year period, including the plug-in charging scenario, SWPT scenarios for charging at home/public parking and/or traffic lights, and DWPT scenarios with or without roadside solar electricity supply and with different regional electricity grid and fuel.

Results indicate that optimal DWPT rollout reduces life cycle GHG & energy by up to 9% and 7% respectively, and roadside solar panels are essential to reduce DWPT life cycle energy and GHG. GHG and energy burdens can break even within 20 years, but costs beyond 20 years.

Based on the results, the following new insights about DWPT deployment are provided for decision making:

- If minimizing life cycle GHG or energy is prioritized as the main design objective, earlier deployment is generally preferable; if life cycle cost is prioritized, later deployment is desired. A monetization of carbon emissions of at least $250 per metric tonne of CO_2 is needed to shift the "pro-cost" deployment to the "pro-GHG" deployment.
- Based on a case study of Washtenaw County in Michigan, a roadway segment with high volume (greater than about 26,000 vehicle counts per day), low speed (slower than 55 miles per hour), and short RSL (shorter than 3 years) should be given a high priority for early-stage DWPT deployment.
- Solar panels and storage batteries are essential for significantly reducing life cycle GHG and energy burdens, so they are recommended to be deployed together with DWPT when the design objective is prioritizing life cycle GHG emissions and energy burdens, with a precaution that they bring additional infrastructure costs.
- Deployment of DWPT in regions with a clean electricity grid, e.g., California, would yield more GHG and energy savings, so earlier and more aggressive deployment is preferred for states or regions with cleaner electricity than Michigan.

7.5 Synergies of Wireless charging technology and Shared Autonomous Battery Electric Vehicles (W+SABEV) (Chapter 6)

A parametric model is developed to explore the synergies of the following four emerging technologies that have been demonstrated to have potential in enhancing sustainable mobility of a fleet of wireless charging shared autonomous battery electric vehicles (W+SABEV). Technologies evaluated through life cycle modeling and simulation include:

- Wireless charging technology
- Shared mobility services (e.g., Uber and Lyft)

- Autonomous driving technology
- Battery electric vehicles

Results indicate that based on the status quo of technology performance using 2018 data, compared to a plug-in charging BEV system:

- A W+SABEV system with wireless charging utility factor <= 5% will pay back GHG emission burdens of additional infrastructure deployment beyond 10 years;
- A W+SABEV system with wireless charging utility factor >= 19% will pay back GHG emission burdens of additional infrastructure deployment within 5 years.

7.6 Recommendations for future research

Agent-based modeling. In Chapter 6, a deterministic life cycle model is developed to evaluate the synergistic effect of four emerging technologies (i.e., wireless charging technology, shared mobility technology, autonomous driving technology, and battery electric vehicle technology) to enhance sustainable mobility. The deterministic model is capable of characterizing the key parameters of the system, including vehicle miles traveled, average fuel economy, battery downsizing, etc. However, in the real world, there is stochastic effect from passenger travel demand and actual traffic congestion. Therefore, an agent-based modeling (ABM) approach would be useful to characterize the real-world stochasticity. Further examination of the W+SABEV system by using ABM can inform decision making in terms of optimizing the layout of wireless charging infrastructure to better serve the passenger travel demand within a region by shared mobility services. An ABM would also help investigate and provide more insights on the effect of randomness of passenger travel demand (e.g., origin, destination, and trip distance) on the reliability of the W+SABEV system. In addition, agent based modeling approach can also incorporate the convenience benefits of stationary wireless charging at home or at work which eliminates the hassle of plugging in. Charging convenience can be quantitatively characterized by the monetary value of saved time. Finally, a policy analysis on the real-time pricing mechanisms can be conducted to examine the impact of different prices of electricity according to supply and demand on the vehicles' decisions on route choices so as to help regulate and decentralize congestion on wireless charging lanes.

Other criteria pollutants. In this dissertation, while different environmental criteria pollutants, such as NO_x, SO_x, of wireless charging infrastructure are examined in the life cycle inventory analysis, the main focus of this dissertation is on the GHG emissions indicator because it is widely used as a sustainability indicator of transportation systems and vehicles. Future research can delve deeper into the environmental impacts of wireless charging technology using different sustainability indicators, such as ozone depletion, acidification, and water scarcity, etc.

End-of-life (EoL) management. A reusable and modular design of DWPT infrastructure embedded in pavement can help facilitate disassembly and recycling of metals and electronics. For example, although the proportion of life cycle GHG burdens from copper wires of wireless charging infrastructure is less than 1% based on the LCI results of this study, the metal after DWPT infrastructure retirement still has economic value. Therefore, recycling of reusable parts may offset some cost and environmental burdens of the initial infrastructure deployment and enhance the life cycle performance of WPT. Given the uncertainty of which parts would be recycled after WPT infrastructure retirement, the EoL stage is excluded in this study, but the recycling opportunities should be investigated once sufficient data become available.

Bi-directional wireless charging. Bi-directional wireless charging, which allows for both vehicle-to-grid (V2G) and grid-to-vehicle (G2V) interactions, offers more opportunities for wireless charging technology to enhance sustainable mobility compared to G2V transmission only. Through V2G, the extra electricity charged by the EVs can be sold back to the electric grid when the electricity demand is high. By feeding back the extra electricity in the EV battery, EV owners will be able to gain financial benefits as well as environmental credits (if the extra electricity is from a clean energy source, e.g., solar). Bi-directional wireless charging facilitates the V2G process by allowing EV owners to feed back the extra electricity while they are driving or idling at traffic lights, as compared to traditional plug-in charging. Therefore, it is worth investigating the implications of wireless V2G technology on the sustainability performance of electric vehicle systems, conduct policy analysis on leveraging the electricity price to incentivize the payback of clean electricity, and examine the role of bi-directional wireless charging technology in this new arena.

Model extrapolation. The current results are obtained based on case studies of Ann Arbor bus systems and Washtenaw County roadway systems. Although sensitivity analyses have been conducted in this work to explore the spatial heterogeneity, it is recommended that future work explores other regions with different travel demand, traffic flow patterns, urban layouts, dominant modes of transportation, and emission intensities of the electric grid to develop more general conclusions and provide further insights.