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Life Cycle Assessment and Tempo-Spatial Optimization of Deploying Dynamic Wireless Charging Technology for Electric Cars

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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 $\approx$ 1.609 km), and pavement RSL shorter than 3 years should be given a high priority for early-stage DWPT deployment.

Keywords: Wireless charging; Dynamic wireless power transfer; Optimization; Deployment plan; Life cycle assessment; Electric vehicle.

1. Introduction

1.1 The role of wireless charging in vehicle electrification

The transportation sector is responsible for over 28% of energy use (Davis et al., 2016) and 27% of greenhouse gas (GHG) emissions (U.S. EPA, 2017a) 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 powered by 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 (Hawkins et al., 2012) 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 (IEA, 2017).

Wireless power transfer (WPT) technology, or more commonly known as wireless charging technology, offers a solution to the EV charging problems. Unlike conventional plug-in charging technology, the wireless charging electric power is typically transferred via an electromagnetic field in an air gap from the coil transmitters embedded in road pavement to the onboard coil receiver installed on the vehicle chassis (Chen et al., 2017; Chen et al., 2018; Jang, 2018; Kan et al., 2016; Onar et al., 2013; Zhang and Mi, 2015; Zhang et al., 2014). 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 (Bi et al., 2016b; Lin et al., 2014).

1.2 Pros and cons of wireless charging

In addition to the aforementioned benefits of charging convenience and widespread availability, other 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 (Choi et al., 2015; Suh, 2010; Suh and Gu, 2011) 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 (Bi et al., 2016a; Bi et al., 2016b; Bi et al., 2015). 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 (Bi et al., 2016a). 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 (Jeong et al., 2018). Therefore, battery life is also incorporated when calculating battery life cycle burdens.

- *Boost EV market penetration*. 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 (Lin et al., 2014). 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 roadside 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 renewable energy and reducing use-phase emission and energy burdens.

Despite the benefits of wireless charging, the apparent downsides and challenges regarding the deployment and technology 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 (Bi et al., 2016b). There are 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.

1.3 Research objectives and highlights

This study 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 (Chen et al., 2016; Quinn et al., 2015) 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 (Lin et al., 2014) 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 (Bi et al., 2015). 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 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 (MDOT, 2017b) 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.

2. Methods

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 (Zhang, 2009). 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 paper) 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 (Bi et al., 2015; Kim et al., 2016). 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 (Quinn et al., 2015). 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 the Appendix.

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 $\approx$ 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) (MDOT, 2017b). 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) (U.S. EPA, 2016). 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 (MDOT, 2017a).

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 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 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 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 (Bi et al., 2015). 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.

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 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 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.

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$$F = \sum_{s=1}^{11} \varphi_s \tag{1}$$

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 (MathWorks Inc., 2015) 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 paper. 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*.

$$\boldsymbol{X}'' = \left\{ x_j'' \mid x_j'' = 0, 1, 2, 3, ..., 20 \right\} \quad j = 1, 2, ..., 154 \tag{2}$$

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 (Walter, 2017). 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.

$$\theta_i \le c_i \text{ for } \forall i \in \{1, 2, ..., 20\} \tag{3}$$

A highlight of this charging infrastructure optimization problem is that it not only optimizes the spatial deployment as many other spatial-only optimization studies (Chen et al., 2016; Hwang et al., 2017; Ko and Jang, 2013; Liu and Song, 2017; Shahraki et al., 2015), 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) (Lin et al., 2014), 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) (U.S. DOT, 2017). 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

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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 $\approx$ 1.609 km) (Bi et al., 2016b; Jones and Onar, 2014; Limb, 2017). 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 (Rubin et al., 2015). 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 (Bi et al., 2016a; Plugless Power, 2015). 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 (U.S. EIA, 2012). 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 (Bi et al., 2016b). 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 (Bi et al., 2015). Given a downsized battery and reduced energy demand, the corresponding battery life is estimated using the experiment-based energy-processed model (Kelly et al., 2015), 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 (Bi et al., 2015). 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.

3. Results

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 1, are presented in this section. The life cycle burdens in terms of costs, GHG emissions, and energy are shown in Figure 1. The corresponding optimal DWPT coverage growth curves for each scenario with DWPT, along with their battery downsizing, are shown in Figure 2.

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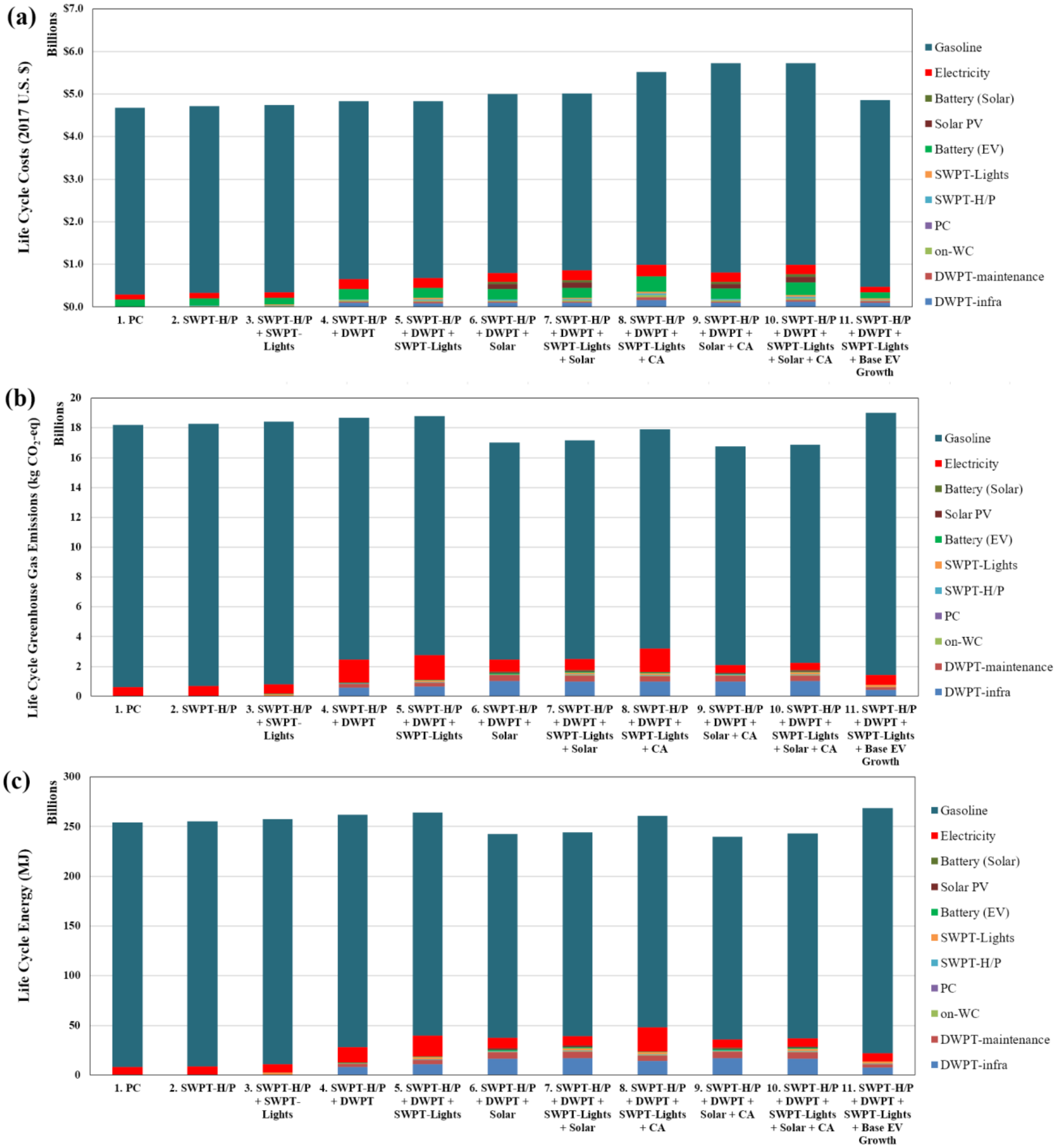

Figure 1. Comparison of eleven scenarios: (a) life cycle costs (in 2017 present-value dollars); (b) life cycle greenhouse gas emissions; and (c) life cycle energy. Note: on-WC = on-board wireless charger installed on the vehicle.

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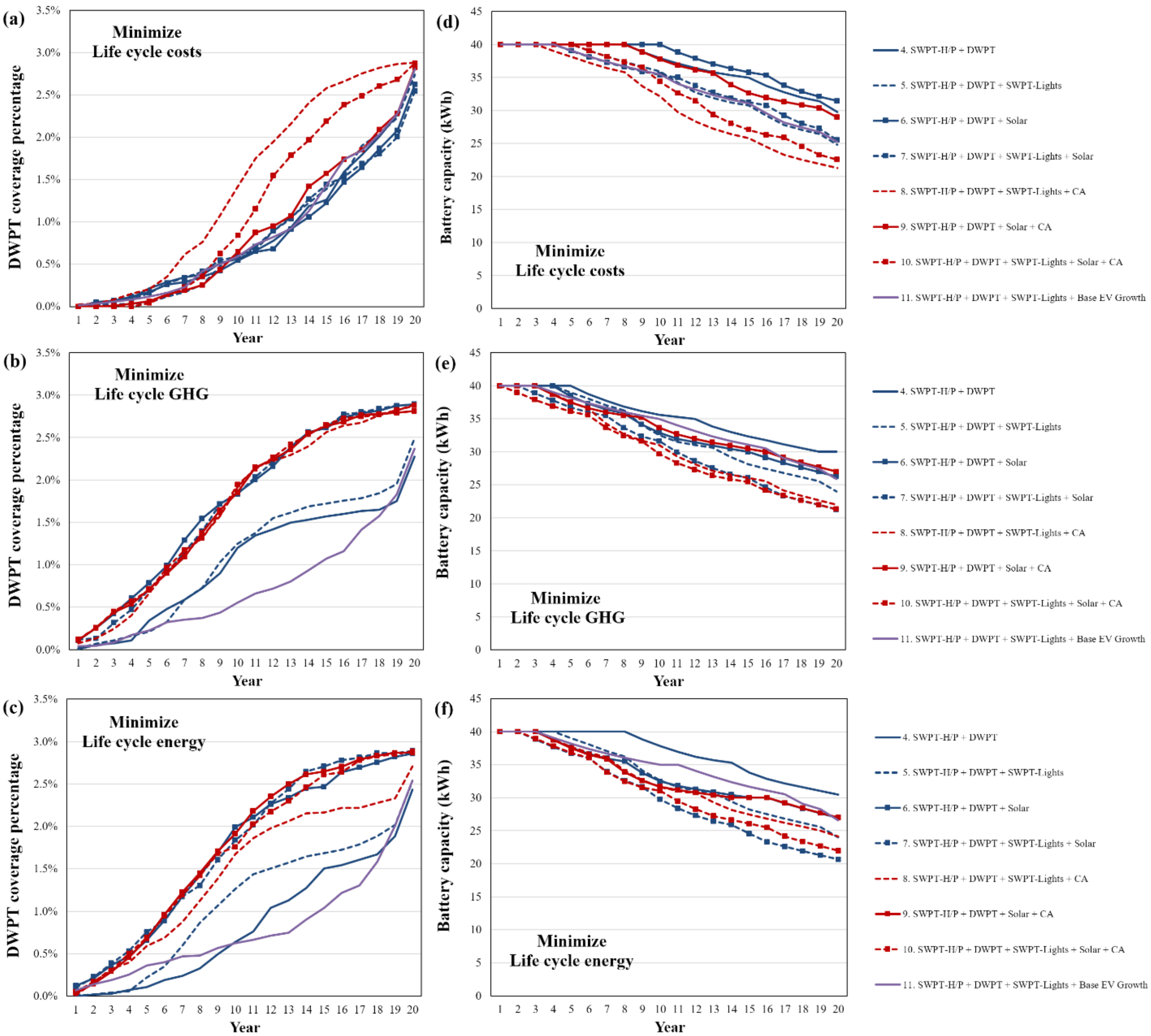

Figure 2. Optimized deployment coverage growth for each scenario with dynamic wireless charging infrastructure, as well as the corresponding battery downsizing trends. Note: GHG = greenhouse gases; and DWPT = dynamic wireless power transfer.

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) (U.S. EPA, 2016). Note that

the GHG and energy graphs share similar patterns as GHG emissions are usually proportional to energy consumption (Bi et al., 2015).

(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 (GasBuddy, 2017; U.S. EIA, 2017).

(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 2 (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 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 2 (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 $\approx$ 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 (Kelly et al., 2015). 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) (U.S. EPA, 2017b), 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.

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 3. 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.

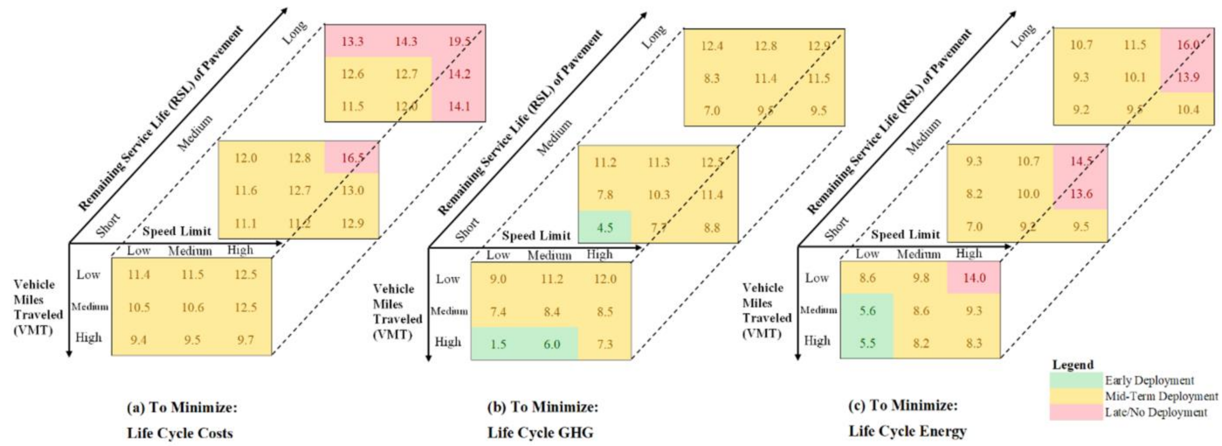

Figure 3. Recommended years to deploy DWPT on roadway segments based on the VMT, speed, and RSL of the segment for each objective of life cycle costs, GHG, or energy. The numbers in the figure indicate the average of deployment years for all segments in the respective categories. The three categories (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 4 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.

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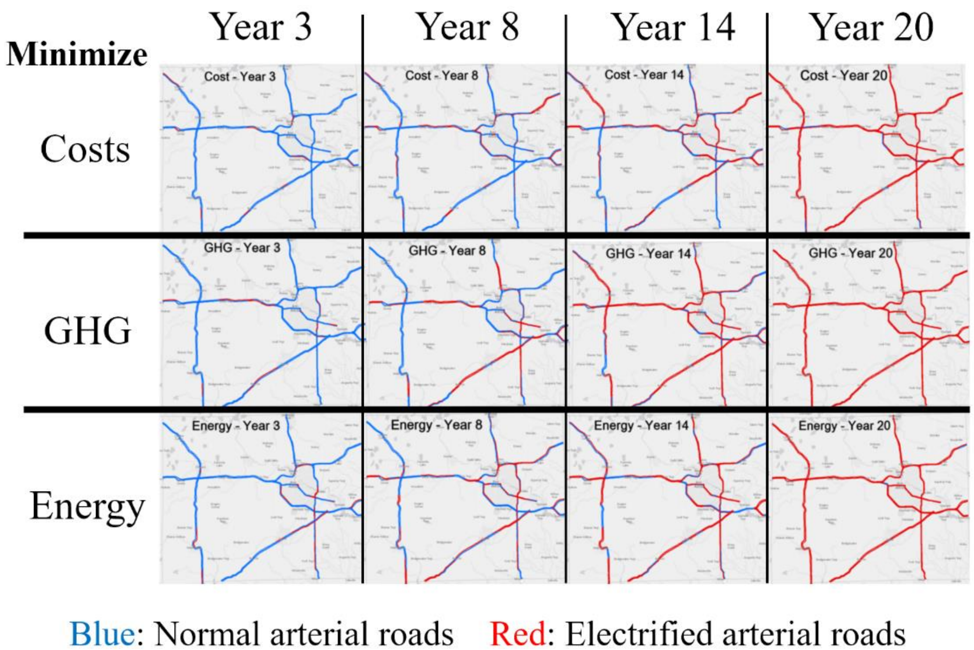

Figure 4. Optimal deployment of dynamic wireless charging infrastructure on arterial roads in Washtenaw County, Michigan, USA, with respect to each objective of minimizing life cycle costs, greenhouse gas (GHG) emissions, and energy burdens.

4. Discussion

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 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 (Limb, 2017). 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.

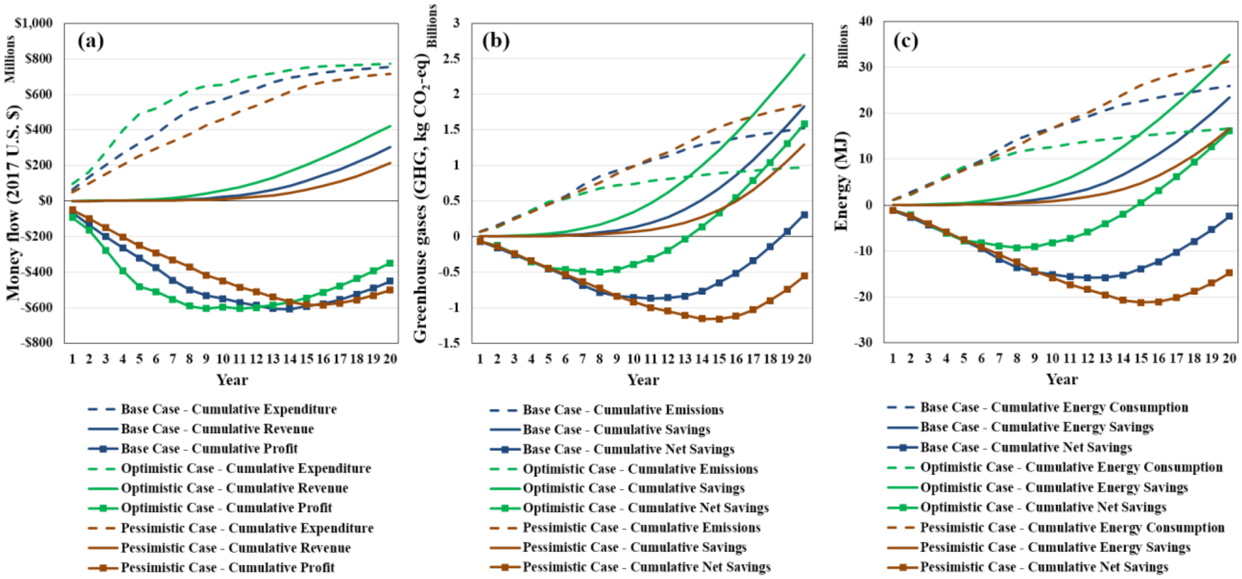

Figure 5. Breakeven analyses: (a) money flow; (b) greenhouse gases (GHG); and (c) energy. Compared to the base case, the optimistic case and the pessimistic case assume 50% and 150% of base infrastructure burdens (cost, GHG, or energy), respectively. The money flow is in 2017 present-value dollars.

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 6. 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.

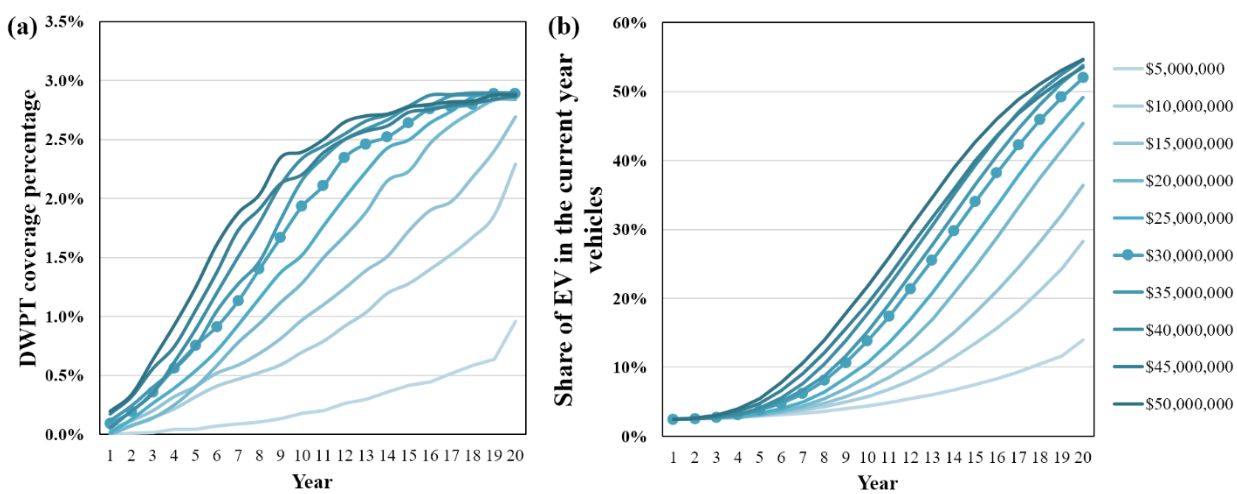

Figure 6. Sensitivity analysis of annual budget for deployment of dynamic wireless charging infrastructure. The annual budget in the base case is \$30 million/year. Note: DWPT = dynamic wireless power transfer; and EV = electric vehicles.

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) (U.S. EPA, 2017b) 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. (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 7, 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) (U.S. EPA, 2017b). 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.

$$F = LCC + LCGHG \times SCC \tag{4}$$

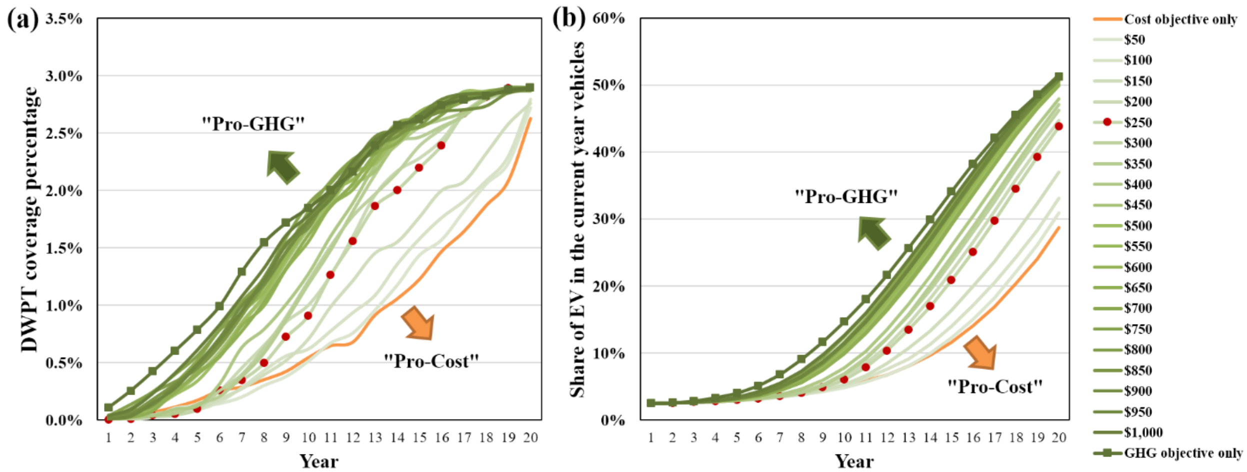

Figure 7. Effect of social cost of carbon (SCC) on the dynamic wireless charging infrastructure deployment and electric vehicle (EV) market share. The unit of SCC is U.S. dollars per metric tonne of CO_2. Note: DWPT = dynamic wireless power transfer; and GHG = greenhouse gases.

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 (Lin et al., 2014); (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 economical 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 (Zivin et al., 2014) 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. 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) roadside 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 roadside 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 (Limb, 2017). 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.
- Roadside 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.

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Appendix A. Supplementary material

A.1. 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 A.1**. 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 (Bi et al., 2015) 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 A.1**.

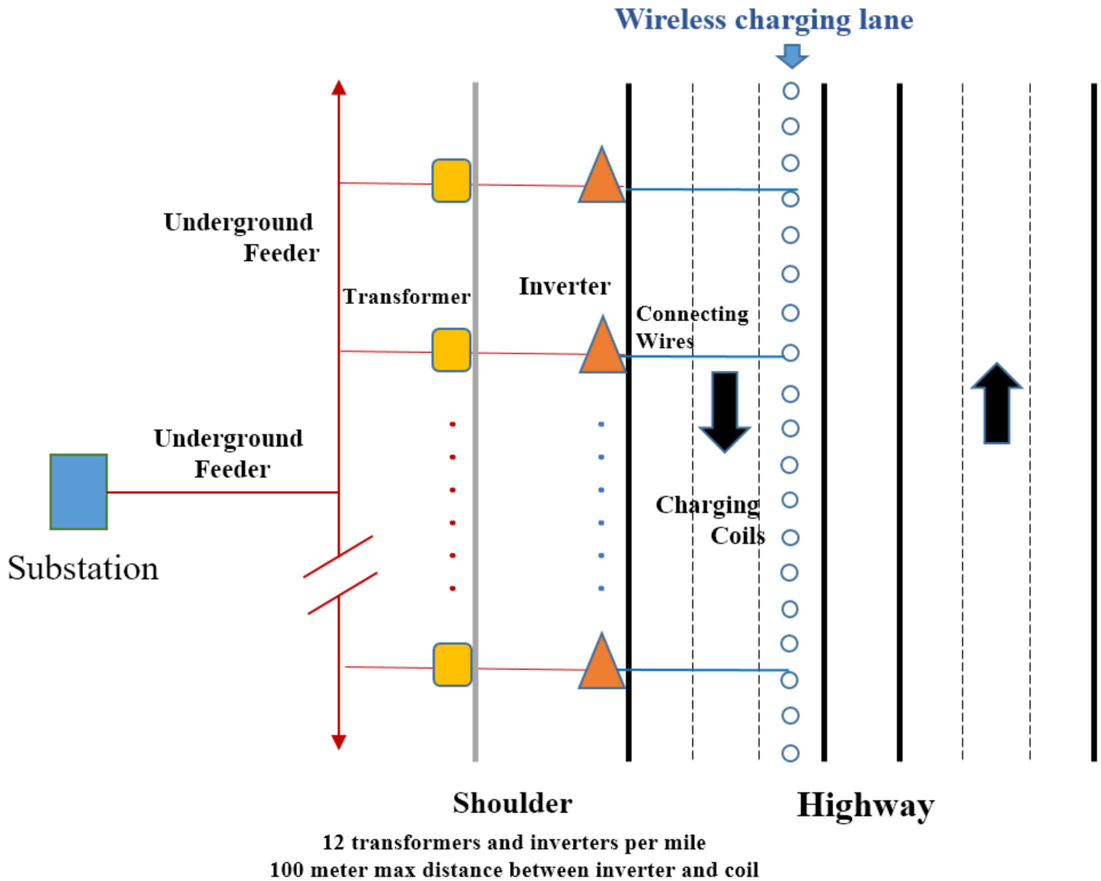

Figure A.1. Schematic of dynamic wireless charging infrastructure. The figure is adapted based on a previous study (Jones and Onar, 2014).

Detailed components and their quantities per lane-mile of dynamic wireless charging infrastructure are summarized in **Table A.1**. The element-wise burdens of each component are summarized in **Table A.2**. Multiplying the values in **Table A.1** with those in **Table A.2** 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.

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Table A.1. 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 (Bi et al., 2015)	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 A.2. 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 $\approx$ 1.609 km.

The fractional breakdown of LCI of dynamic wireless charging infrastructure per lane-mile is shown in **Figure A.2**. And the detailed absolute values of life cycle inventory are summarized in **Table A.3**.

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.

Citation: Zicheng Bi, Gregory A. Keoleian, Zhenhong Lin, Michael R. Moore, Kainan Chen, Lingjun Song, Zhengming Zhao, Life cycle assessment and tempo-spatial optimization of deploying dynamic wireless charging technology for electric cars, Transportation Research Part C: Emerging Technologies, Volume 100, 2019, Pages 53-67,

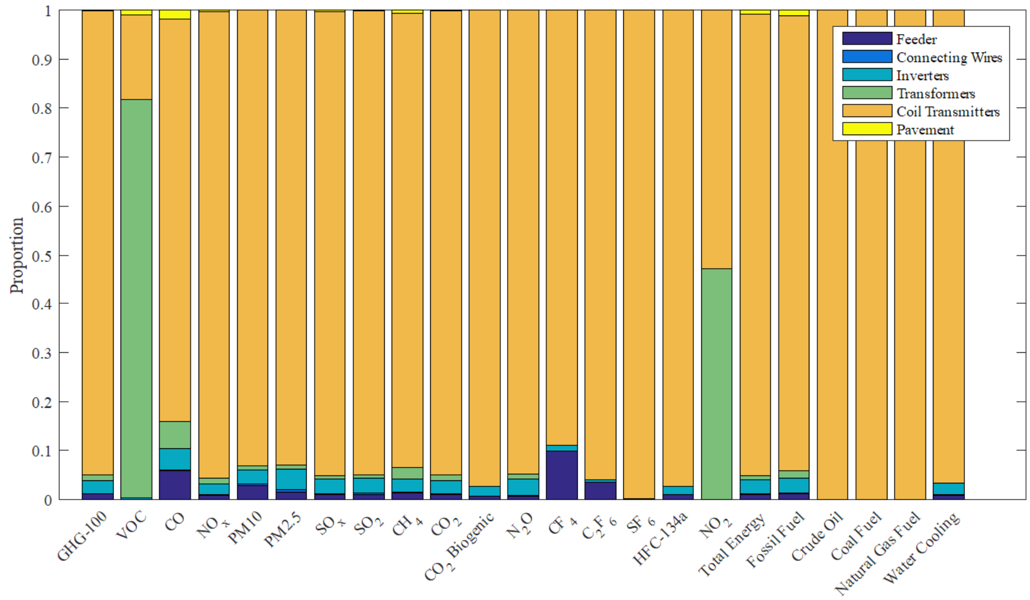

Figure A.2. Fractional breakdown of life cycle inventory results of dynamic wireless charging infrastructure for different metrics.

Table A.3. 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.

A.2. Optimization model and parameters

Table A.4. 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", $s = 1, 2, \ldots, 11$	/

i	Year index, $i = 1, 2, \ldots, 20$, representing each year of the 20-year period	/
j	Road segment index, $j = 1, 2, \ldots, 154$, representing 154 segments of arterial roads in Washtenaw County, Michigan	/
k	Index for each hour of a day, $k = 1, 2, \ldots, 24$	/
θ_i	Annual expense (calculated) on DWPT deployment in a particular year i (U.S. $)	/
c_i	Annual budget constraint (U.S. $)	(Walter, 2017)
σ_s	Coefficients to convert quantities to life cycle burdens, $s = 1, 2, \ldots, 11$ 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.	(Argonne National Laboratory, 2017; Goedkoop et al., 2013; U.S. EPA, 2016)
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 $\boldsymbol{i}$, 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 $\boldsymbol{i}$, 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 ($x''_j = 1, 2, 3, \ldots, 20$) or no deployment in any year ($x''_j = 0$)	/
l_j	The length of a road segment j (miles) measured on map	(ArcGIS, 2017)
r_{ij}	Road repair indicator: If a road segment j is scheduled to be repaired in year $\boldsymbol{i}$, then $r_{ij} = 1$; otherwise $r_{ij} = 0$	(MDOT, 2017a)
R_j	The year of scheduled road repair for road segment j	(MDOT, 2017a)
Λ_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 $\boldsymbol{i}$	(Zhang, 2009)

ε_{m}	Proportion of annual maintenance burden relative to the DWPT deployment burden, which is assumed to be 2% ($\varepsilon_{\mathrm{m}} = 0.02$)	/
L	Life of a component in the unit of miles. L_X where X can be: - L_{EV} = 160,000 miles (electric vehicle) - $L_{\mathrm{onWC}} = L_{\mathrm{EV}}$ (on-board wireless charger) - $L_{\mathrm{PC}} = L_{\mathrm{EV}}$ (plug-in charger) - $L_{\mathrm{SWPTHP}} = L_{\mathrm{EV}}$ (SWPT at home/public parking) - L_{bat_i} modeled (fleet-average battery life in year i)	(Argonne National Laboratory, 2017; Kelly et al., 2015)
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)	(Stoppato, 2008; U.S. DOT, 2017; Zhang, 2009)
VMT_{EV_i}	Vehicle miles traveled in year i of all electric vehicles on the road segments	(MDOT, 2017b)
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	(Kelly et al., 2015)
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)	(National Renewable Energy Laboratory, 2017)
η_{module}	Solar module efficiency = 16%	(Stoppato, 2008)

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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%	(Bi et al., 2015)
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	(MDOT, 2017b)
$e_{\text{DW}_{ij}}$	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	(MDOT, 2017b)
ξ_i	Average fuel economy of conventional gasoline vehicles in year i (miles/gallon)	(U.S. DOT, 2017)

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”.

$$F = \sum_{s=1}^{11} \varphi_s \tag{A.1}$$

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 (OMB, 2017). All costs are reported in present-value dollars.

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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.

$$\boldsymbol{X} = \left\{ x_{ij} \mid x_{ij} = 0, 1 \right\} \quad i = 1, 2, ..., 20; \; j = 1, 2, ..., 154 \quad \text{“Status”} \tag{A.2}$$

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.

$$\boldsymbol{X}' = \left\{ x'_{ij} \mid x'_{ij} = 0, 1 \right\} \quad i = 1, 2, ..., 20; \; j = 1, 2, ..., 154 \quad \text{“Deploy”} \tag{A.3}$$

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 ($x''_j = 0$):

$$\boldsymbol{X}'' = \left\{ x''_j \mid x''_j = 0, 1, 2, 3, ..., 20 \right\} \quad j = 1, 2, ..., 154 \tag{A.4}$$

Constraint:

The constraint limits the annual deployment of DWPT infrastructure within the annual budget. Eq. (A.6) 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 ($\sum_{j=1}^{154} x'_{ij} r_{ij} l_j \Lambda_i$) are credited.

$$\theta_i \le c_i \quad \text{for } \forall i \in \{1, 2, ..., 20\} \tag{A.5}$$

$$\text{where } \theta_i = \sum_{j=1}^{154} (\sigma_{1_i} x'_{ij} l_j - x'_{ij} r_{ij} l_j \Lambda_i) \tag{A.6}$$

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 Λ_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

$$\varphi_1 = \sum_{i=1}^{20} \sum_{j=1}^{154} \left(\frac{20 - i + 1}{Y_{\text{DWPT}}} (\sigma_{1_i} x'_{ij} l_j - x'_{ij} r_{ij} l_j \Lambda_i) + p_{ij} \right) \tag{A.7}$$

$$\text{where } p_{ij} = x'_{ij} \cdot \frac{\max\{R_j - i, 0\}}{Y_{\text{pavement}}} \cdot l_j \beta_i \tag{A.8}$$

Side note:

Life of a new pavement is assumed to be 20 years (Zhang, 2009). 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

$$\varphi_2 = \sum_{i=1}^{20} \sum_{j=1}^{154} \sigma_{2_i} x_{ij} l_j \tag{A.9}$$

$$\text{where } \sigma_{2_i} = \sigma_{1_i} \varepsilon_{\text{m}} \tag{A.10}$$

Component 3: Onboard wireless chargers (on-WC)

$$\varphi_3 = \sum_{i=1}^{20} VMT_{\text{EV}_i} \frac{\sigma_{3_i}}{L_{\text{onWC}}} \tag{A.11}$$

Component 4: Plug-in chargers (PC)

$$\varphi_4 = \sum_{i=1}^{20} VMT_{\text{EV}_i} \frac{\sigma_{4_i}}{L_{\text{PC}}} \tag{A.12}$$

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

$$\varphi_5 = \sum_{i=1}^{20} VMT_{\text{EV}_i} \frac{\sigma_{5_i}}{L_{\text{SWPTHP}}} \tag{A.13}$$

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

$$\varphi_6 = \sum_{i=1}^{20} \sigma_{6_i} N_{\text{int}} l_{\text{int}} \frac{20 - i + 1}{Y_{\text{SWPTL}}} \tag{A.14}$$

Component 7: Battery (electric vehicle)

$$\varphi_7 = \sum_{i=1}^{20} BatCap_{\text{cum}_i} VMT_{\text{EV}_i} \frac{\sigma_{7_i}}{L_{\text{bat}_i}} \tag{A.15}$$

$$\text{where } L_{\text{bat}_i} = \frac{\min\{Y_{\text{EV}}, \frac{E_{\text{cell}}}{\alpha_i}\}}{Y_{\text{EV}}} \cdot L_{\text{EV}} \tag{A.16}$$

Side note 1: $BatCap_i = \frac{E_{\text{demand}_i} - E_{\text{charged}_i}}{\omega}$ is converted to $BatCap_{\text{cum}_i}$ 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. The charging time of dynamic charging is determined from dividing the total charging distance (miles) by the average vehicle speed (miles per hour) on charging lanes. The charging time at traffic lights is determined by statistically summarizing the time spent at traffic intersections with charging availability.

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 (Kim, 2014; Kim and Wallington, 2013). 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

$$\varphi_8 = \sum_{i=1}^{20} \sum_{j=1}^{154} \frac{20 - i + 1}{Y_{\text{solar}}} \sigma_{8_i} x'_{ij} l_j \lambda_{\text{area}} \tag{A.17}$$

$$\text{where } \lambda_{\text{area}} = \frac{\psi}{\phi \eta_{\text{module}}} \tag{A.18}$$

Component 9: Battery (solar)

$$\varphi_9 = \sum_{i=1}^{20} \sum_{j=1}^{154} \sigma_{9_i} \pi_{ij} l_j \lambda_{\text{bcap}} \tag{A.19}$$

$$\text{where } \lambda_{\text{bcap}} = \frac{\psi \tau_{\text{night}} \mu}{\eta_{\text{bat}}} \tag{A.20}$$

Eq. (A.20) 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

$$\varphi_{10} = \sum_{i=1}^{20} \sum_{j=1}^{154} \sum_{k=1}^{24} (\sigma_{10_{ik}} v_{ijk} (e_{\mathrm{DW}_{ij}} + e_{\mathrm{SWL}_{ij}} + e_{HP_{ij}})) \tag{A.21}$$

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

$$\varphi_{11} = \sum_{i=1}^{20} \sum_{j=1}^{154} \sigma_{11_i} \frac{VMT_{\mathrm{CV}_{ij}}}{\xi_i} \tag{A.22}$$

Other model details:

The learning curve of DWPT is shown in **Figure A.3**. 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 (Rubin et al., 2015).

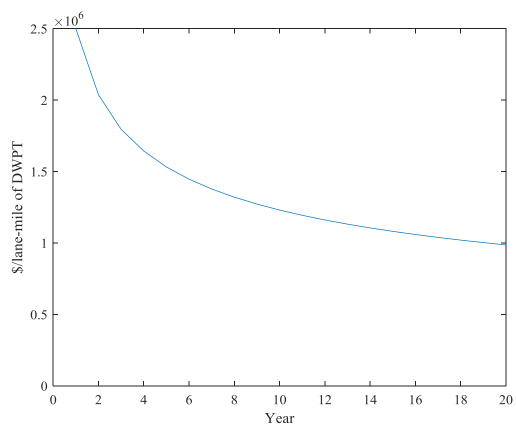

Figure A.3. Learning curve of dynamic wireless power transfer (DWPT) infrastructure.

The extra EV sales boosted by increasing deployment of DWPT infrastructure compared to business-as-usual case is shown in **Figure A.4**. The business-as-usual case assumes EV sales share increases from 2% in 2020 to 24% in 2050 (Lin et al., 2014). 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) (U.S. DOT, 2017).

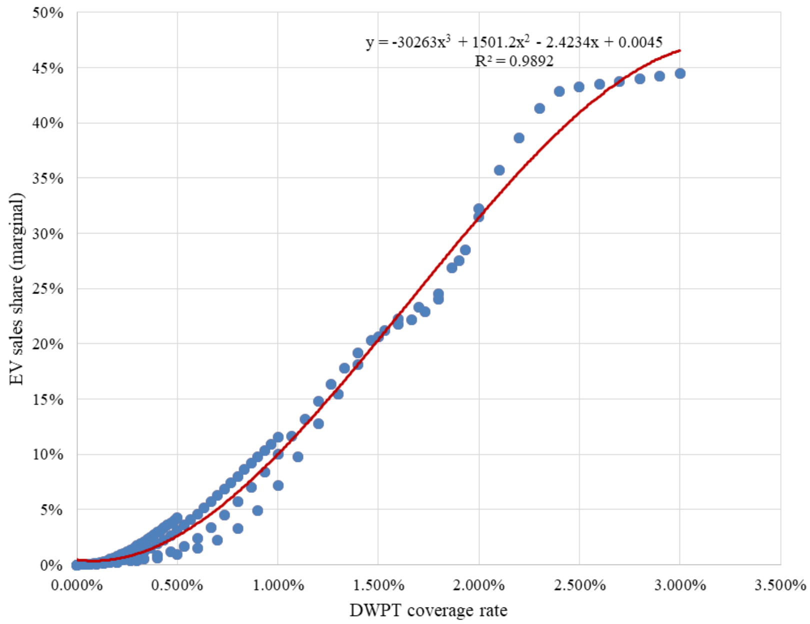

Figure A.4. Extra sales share of electric vehicles (EV) boosted by increasing deployment of dynamic wireless power transfer (DWPT) infrastructure.

A.3. Supplementary results

Temporal change in average energy consumption rate of all electric vehicles in operation is shown in **Figure A.5**.

Citation: Zicheng Bi, Gregory A. Keoleian, Zhenhong Lin, Michael R. Moore, Kainan Chen, Lingjun Song, Zhengming Zhao, Life cycle assessment and tempo-spatial optimization of deploying dynamic wireless charging technology for electric cars, Transportation Research Part C: Emerging Technologies, Volume 100, 2019, Pages 53-67,

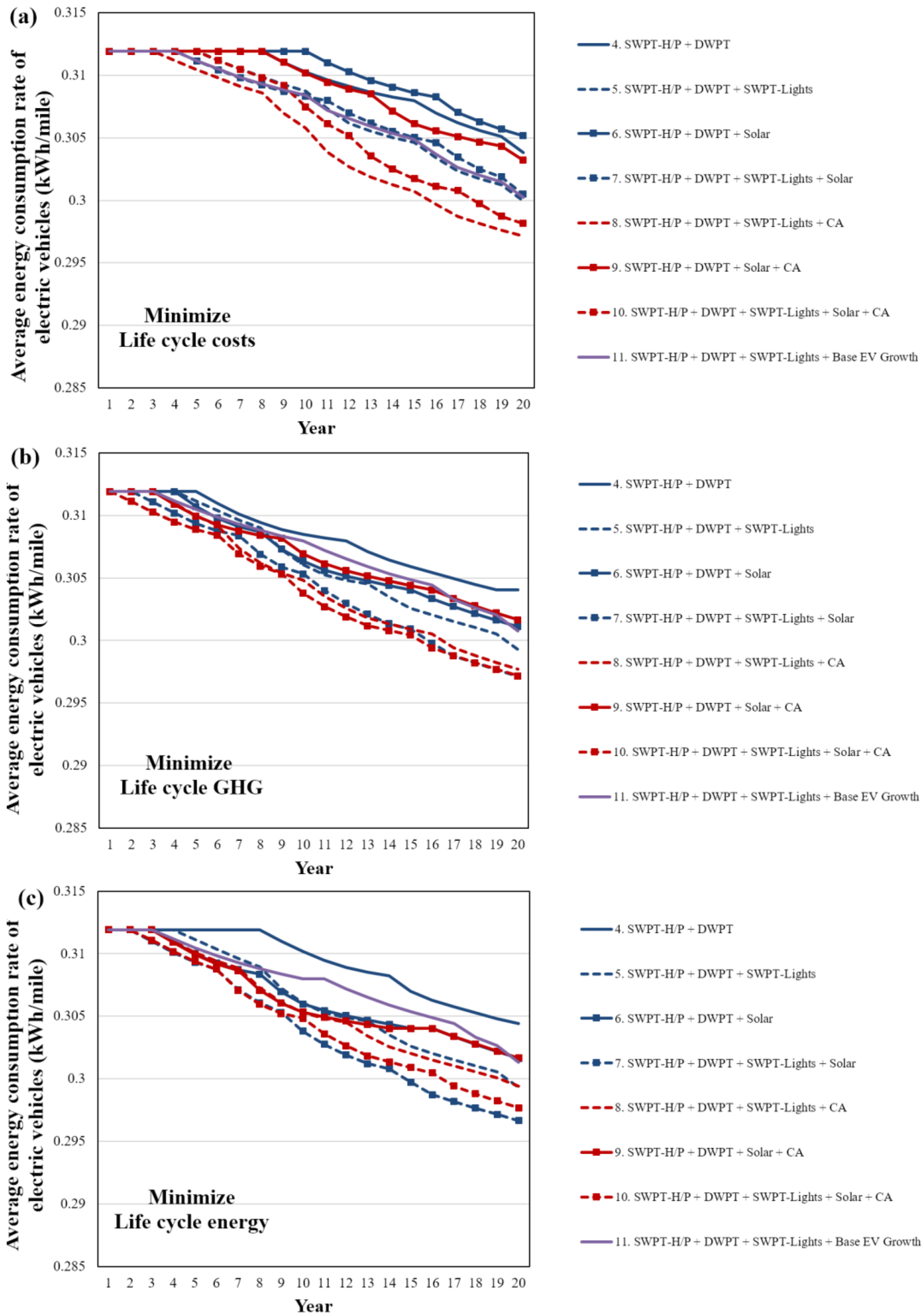

Figure A.5. Temporal change in average energy consumption rate of all electric vehicles in operation. Note: GHG = greenhouse gases.

Temporal change in theoretical battery life of all electric vehicles in operation is shown in **Figure A.6**.

Citation: Zicheng Bi, Gregory A. Keoleian, Zhenhong Lin, Michael R. Moore, Kainan Chen, Lingjun Song, Zhengming Zhao, Life cycle assessment and tempo-spatial optimization of deploying dynamic wireless charging technology for electric cars, Transportation Research Part C: Emerging Technologies, Volume 100, 2019, Pages 53-67,

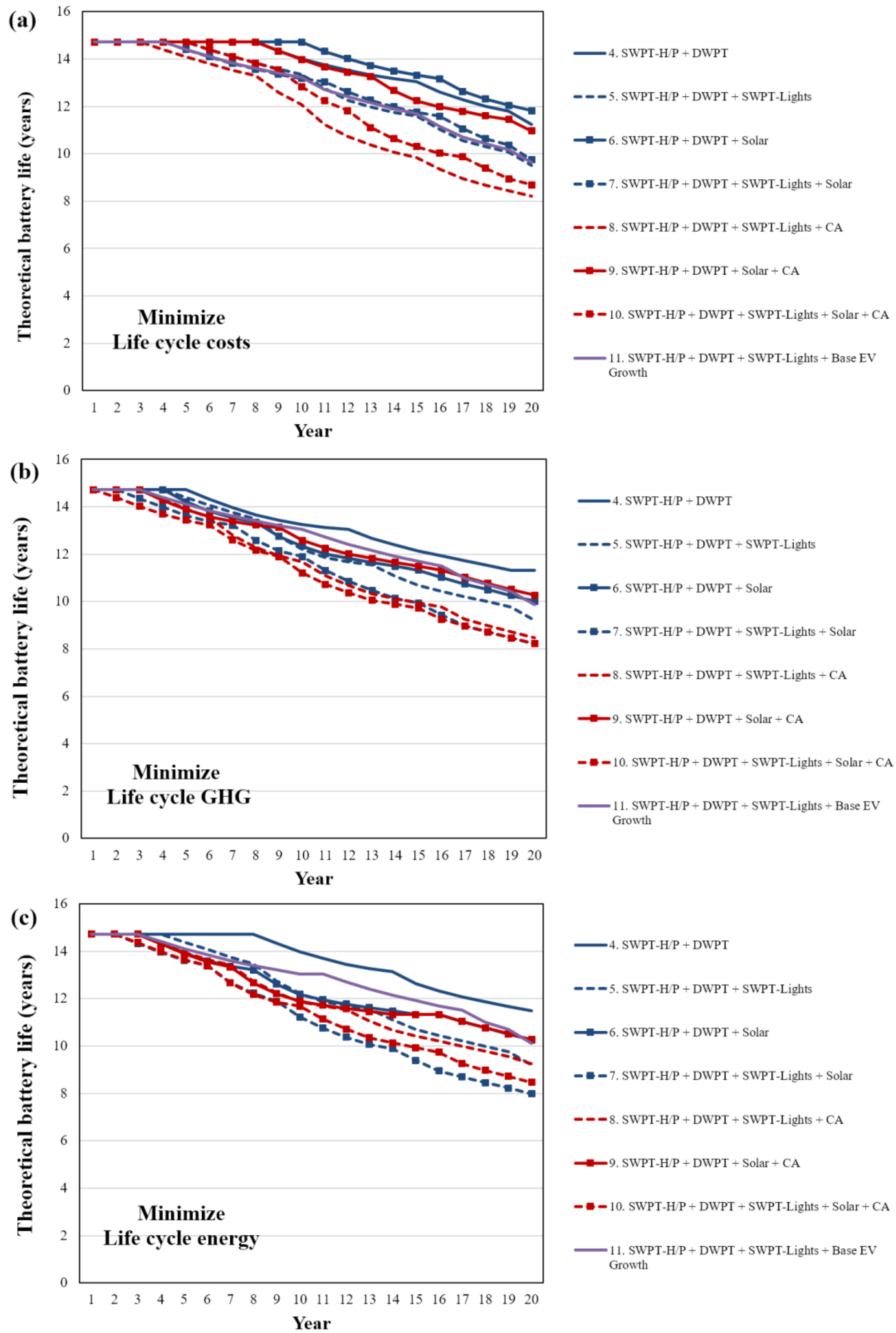

Figure A.6. Temporal change in theoretical battery life of all electric vehicles in operation. Note: GHG = greenhouse gases.

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