Wireless Charger Deployment for an Electric Bus Network: A Multi-Objective Life Cycle Optimization

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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 paper 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.

**Keywords:** Wireless charging; Life cycle optimization; Life cycle assessment; Electric vehicle; Charger siting; Sustainability
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 article 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 paper is organized as follows. Section 2 describes methods of constructing the optimization model framework. Section 3 presents first the optimization results when solving for each objective individually, then the multi-objective results. Section 4 discusses the results based on several sensitivity, uncertainty, and scenario analyses. Finally key conclusions and takeaways are summarized in Section 5.

2. Methods

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 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 2^{83} 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.

![Wireless Charging Infrastructure](image)

**Figure 1.** Overview of the multi-objective life cycle optimization model. GHG = greenhouse gas.

### 2.2 Details of the optimization model

#### 2.2.1 System equations

Eqs.(1)–(8) specify the objective function, constraints, and key derivations of the
optimization model, and Table 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.

As mentioned in Section 2.1, heuristic algorithms are appropriate for solving this discrete
optimization problem with a large decision space of $2^{83}$ 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 paper, 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. (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.

\[
\begin{align*}
\min F &= \alpha_1 \sum_{i=1}^{\text{num}_{\text{bs}}} s(i) + \alpha_2 \sum_{i=1}^{\text{num}_{\text{bs}}} v(i) + \alpha_3 n_{\text{onWC}} + \sum_{r=0}^{24} \sum_{i=1}^{\text{num}_{\text{bs}}} n_{\text{rep}}(r,i) \text{BatCap}(r) \text{BatRep}(r,i) + \alpha_5 E_{\text{operation}} + \alpha_6 E_{\text{depot}} \\
\end{align*}
\]

Constraints or key definitions:

Eq. (2) defines a matrix of dwell time (minutes) at each stop \( i \) for each route \( r \).

\[
T(i,r) = \tau \quad \text{where } i = 1, 2, ..., \text{num}_{\text{bs}}; \ r = 1, 2, ..., \text{num}_{\text{rs}}; \ \tau \geq 0
\]  

Eq. (3) defines the binary decision variable vector, where 0 means “not deploy wireless chargers at stop \( i \)” and 1 means “deploy”.

\[
s(i) \in \{0,1\} \quad \text{where } i = 1, 2, ..., \text{num}_{\text{bs}} \quad \text{(Decision variables)}
\]

Eq. (4) defines the vector of number of power transmitters at each bus stop.

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

Eq. (5) calculates the cumulative daily electricity demand (kWh) for each route \( r \) until stop \( k \) for battery sizing purpose.

\[
e_{k+1}(r) = \begin{cases} 
e_k(r) + ECR_{\text{base}} d_k(r) - \eta_r \eta_{b,r} P(\frac{\tau}{60}) & \text{if charger available} \\
e_k(r) + ECR_{\text{base}} d_k(r) & \text{if charger not available}
\end{cases}
\]

Eq. (6) calculates battery capacity for each route in kWh.

\[
\text{BatCap}(r) = \max \{(\max(e(r)) - e_0) / (SOC_{\text{initial}} - SOC_{b}), \ 25 \text{ kWh}\}
\]

Eq. (7) calculates the adjusted energy consumption rate (kWh/mile) for each route \( r \) by considering the lightweighting effects of battery downsizing.
\[ ECR'(r) = ECR_{\text{base}} \left[ 1 - \frac{BatWgt_{\text{base}} - BatCap(r) / \rho + R_{\text{adj}}(r)}{BusWgt_{\text{base}}} \cdot \sigma \right] \] (7)

Eq. (8) calculates the battery state of charge (SOC) at stop \( k \) for each route \( r \).

\[
SOC_{k+1}(r) = \begin{cases} 
SOC_k(r) - \frac{ECR'(r)d_k(r)}{BatCap(r)} + \eta \cdot \eta_{\text{b}} \cdot \frac{P(r)}{60} & \text{if } SOC_{k+1}(r) \leq SOC_{\text{ub}} \\
SOC_{\text{ub}} & \text{otherwise}
\end{cases}
\] (8)

where \( SOC_0 = SOC_{\text{initial}} = 0.9 \)

Table 1. Definitions of variables and parameters.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>( F )</td>
<td>Objective function, which can be life cycle costs (U.S. $), greenhouse gas emissions (kg CO(_2)-eq), or energy consumption (MJ)</td>
<td>/</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>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</td>
<td>[6, 7, 10]</td>
</tr>
<tr>
<td>( \alpha_2 )</td>
<td>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</td>
<td>[6, 7, 10]</td>
</tr>
<tr>
<td>( \alpha_3 )</td>
<td>Coefficient of burden for the 100 kW on-board wireless charger, can be $5,000/unit, 1,717 kg CO(_2)-eq/unit, or 29,500 MJ/unit</td>
<td>[6, 7, 10]</td>
</tr>
<tr>
<td>( \alpha_{4,t} )</td>
<td>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)</td>
<td>[6, 7]</td>
</tr>
<tr>
<td>( \alpha_5 )</td>
<td>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</td>
<td>[17-19]</td>
</tr>
<tr>
<td>( \alpha_6 )</td>
<td>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</td>
<td>[17-19]</td>
</tr>
<tr>
<td>( t )</td>
<td>A particular year, ( t = 0, 1, 2, ..., 24 )</td>
<td>/</td>
</tr>
<tr>
<td>( \tau )</td>
<td>Dwell time at a particular stop (minutes), ( \tau \geq 0 )</td>
<td>/</td>
</tr>
<tr>
<td>( i )</td>
<td>The stop ID number, where ( i = 1, 2, ..., 83 )</td>
<td>/</td>
</tr>
<tr>
<td>( s )</td>
<td>Vector of decision variables, ( s(i) \in {0, 1} ) where 0 = not deploy wireless chargers at stop ( i ); 1 = deploy</td>
<td>/</td>
</tr>
<tr>
<td>( \nu )</td>
<td>Vector of number of power transmitters (i.e., the variable part of off-board charging infrastructure) at each stop, ( \nu(i) \in {0, 1, 2} )</td>
<td>/</td>
</tr>
<tr>
<td>( r )</td>
<td>The ID number of bus route, ( r = 1, 2, ..., 7 )</td>
<td>/</td>
</tr>
<tr>
<td>( n_{\text{onWC}} )</td>
<td>Number of onboard wireless chargers, which is equal to the number of buses, ( n_{\text{onWC}} = 29 )</td>
<td>/</td>
</tr>
<tr>
<td>( \text{num}_{\text{bs}} )</td>
<td>Number of bus stops (83)</td>
<td>/</td>
</tr>
<tr>
<td>( \text{num}_{\text{rts}} )</td>
<td>Number of bus routes (7)</td>
<td>/</td>
</tr>
<tr>
<td>( \text{BatCap} )</td>
<td>Vector of battery capacity for each route (kWh)</td>
<td>/</td>
</tr>
<tr>
<td>( \text{BatRep} )</td>
<td>Matrix of battery replacement for each route ( r ) at each year ( t ), ( \text{BatRep}(r, t) \in {0, 1} ) where ( 1 = \text{replace} ); ( 0 = \text{not replace} )</td>
<td>/</td>
</tr>
<tr>
<td>( E_{\text{operation}} )</td>
<td>The total electricity charged during bus operation (measured at grid, kWh)</td>
<td>/</td>
</tr>
</tbody>
</table>
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. (2), an 83×7 matrix $T$ 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 $T$ 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.

Note: 1 mile $\approx 1.609$ km.
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., \( \sum_{i=1}^{83} s(i) \). On the other hand, the variable length at a particular stop is determined by Eq. (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., \( \sum_{i=1}^{83} v(i) \).

### 2.2.3 Battery life and degradation

Batteries for each route are sized by Eq. (5) and Eq. (6). First, the cumulative daily battery energy demand for each route is calculated using Eq. (5). Battery capacity is calculated using Eq. (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. (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 \( \sigma \) [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. (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. (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.

\[
\text{Cycles} = \left( \frac{\text{DoD}}{145.71} \right)^{(-1/0.6844)}
\]

(9)

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

**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 CO₂/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 CO₂ and energy intensities of the electricity generation of the Great Lakes/Mid-Atlantic region are calculated and shown in Figure 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 CO₂ 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 \(\alpha_5\) and \(\alpha_6\) in Eq. (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 \(\alpha_5\) and \(\alpha_6\) are provided in Table 1.
3. Results

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 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 3. The selected bus stops at the optimal life cycle costs as an example are mapped in Figure 4. The SOC curves for each route at life cycle cost optima can be found in the Supporting Information.
Table 2. Single-objective optimization results.

<table>
<thead>
<tr>
<th>Objective function ($, kg CO₂-eq, or MJ)</th>
<th>Cost</th>
<th>GHG</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>9,644,967</td>
<td>45,182,578</td>
<td>582,657,784</td>
<td></td>
</tr>
</tbody>
</table>

| Number of stops selected out of 83 stops | 42 | 55 | 52 |

<table>
<thead>
<tr>
<th>Battery capacity (kWh)</th>
<th>Route 1</th>
<th>Route 2</th>
<th>Route 3</th>
<th>Route 4</th>
<th>Route 5</th>
<th>Route 6</th>
<th>Route 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route 1</td>
<td>68</td>
<td>84</td>
<td>105</td>
<td>57</td>
<td>85</td>
<td>25</td>
<td>79</td>
</tr>
<tr>
<td>Route 2</td>
<td>68</td>
<td>74</td>
<td>100</td>
<td>48</td>
<td>56</td>
<td>25</td>
<td>65</td>
</tr>
<tr>
<td>Route 3</td>
<td>68</td>
<td>74</td>
<td>100</td>
<td>48</td>
<td>56</td>
<td>25</td>
<td>65</td>
</tr>
<tr>
<td>Route 4</td>
<td>68</td>
<td>74</td>
<td>100</td>
<td>48</td>
<td>56</td>
<td>25</td>
<td>65</td>
</tr>
<tr>
<td>Route 5</td>
<td>68</td>
<td>74</td>
<td>100</td>
<td>48</td>
<td>56</td>
<td>25</td>
<td>65</td>
</tr>
<tr>
<td>Route 6</td>
<td>68</td>
<td>74</td>
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Note: GHG = greenhouse gas.

Figure 3. Breakdown of optimal life cycle burdens for the single objective of life cycle costs, greenhouse gas (GHG) emissions, and energy consumption.
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 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 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.

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.

Figure 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 gas.

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. Discussion

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 6.

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 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 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 gas.
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 Supporting Information.

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 – 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 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 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 8](image)

**Figure 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.

### 4.3 Scenario analysis

#### 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. (10),

$$ F_G = F_{\text{cost}} + F_{\text{GHG}} \cdot SCC \cdot \frac{1 \text{ t}}{1000 \text{ kg}} $$

where $F_G$ is the grand objective function ($\)$, $F_{\text{cost}}$ is the objective function of life cycle costs ($\)$, $F_{\text{GHG}}$ is the objective function of life cycle GHG emissions (kg), $SCC$ is the social cost of carbon ($/\text{metric tonne CO}_2$). 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 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 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 9. Scenario analysis of the social cost of carbon.](image)

### 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 [Supporting Information](#).
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.

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Appendix A. Supplementary material

Supplementary data (Supporting Information) associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.apenergy.2018.05.070.

References


Glossary

AVERT: the AVoided Emissions and geneRation Tool

DoD: Depth of discharge

ECR: Energy consumption rate

EV(s): Electric vehicle(s)

GA: Genetic algorithm

GHG: Greenhouse gas

ID: Identification

LCA: Life cycle assessment

LCCA: Life cycle cost analysis

LCO: Life cycle optimization

OLEV: Online electric vehicle

SCC: Social cost of carbon
SOC: State of charge
U.S. EIA: the U.S. Energy Information Administration
U.S. EPA: the U.S. Environmental Protection Agency
WPT: Wireless power transfer