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Article

Energy Logistics Cost Study for Wireless Charging Transportation Networks

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Abstract: Many cities around the world encourage the transition to battery-powered vehicles to minimize the carbon footprint of the transportation sector. Deploying large-scale wireless charging infrastructures to charge electric transit buses when loading and unloading passengers have become an effective way to reduce emissions. The standard plug-in electric vehicles have a limited amount of power stored in the battery, resulting in frequent stops to refill the energy. Optimal siting of wireless charging bus stops is essential to reducing these inconveniences and enhancing the sustainability performance of a wireless charging bus fleet. Wireless charging is an innovation of transmitting power through electromagnetic induction to portable electrical devices for energy renewal. Online Electric Vehicle (OLEV) is a new technology that allows the vehicle to be charged while it is in motion, thus removing the need to stop at a charging station. Developed by the Korea Advanced Institute of Science and Technology (KAIST), OLEV picks up electricity from power transmitters buried underground. This paper aims to investigate the cost of the energy logistics for the three types of wireless charging networks: stationary wireless charging (SWC), quasi-dynamic wireless charging (QWC), and dynamic wireless charging (DWC), deployed at stops and size of battery capacity for electric buses, using OLEV technology for a bus service transit in the borough of Manhattan (MN) in New York City (NYC).

Keywords: electric buses; wireless charging; dynamic wireless charging electric vehicle; New York City

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1. Introduction

In recent years, the need to develop alternative solutions to traditional energy sources, such as fossil fuels, has become imperative for sustainable cities. Thus, Electric Vehicles (EVs) reduce the need for fossil fuels and provide a better living environment. Since transit is the main source of fuel consumption, the development of electric buses has become a priority.

Earlier research focused on plug-in and conductive solutions for charging the EVs and has considered the challenges of incorporating this technology into electricity networks [1]. Plug-in EVs have a limited travel span and require heavy and large batteries. The standard plug-in electric vehicles have a reduced amount of power stored in the battery, resulting in recurrent stops to refill the power. Therefore, conductive charging strategies involve long waiting times, limiting the pertinence of EVs compared to fuel-combustion-powered vehicles.

More recent studies have shown the benefits and advantages of pure electric vehicles, compared to fuel combustion-based cars or hybrid EVs, in terms of their environmental effects [2]. Nevertheless, these benefits may be offset by the limited amounts of energy stored in their batteries. To make EVs even worse, charging with the fastest charger requires at least 30 min [3]. To fill this gap, the use of Remote Charging Technology, also known as wireless charging [4,5], has been tested and implemented. Wireless charging is an innovation of transmitting power through electromagnetic induction to portable electrical devices to ensure optimized energy renewal.

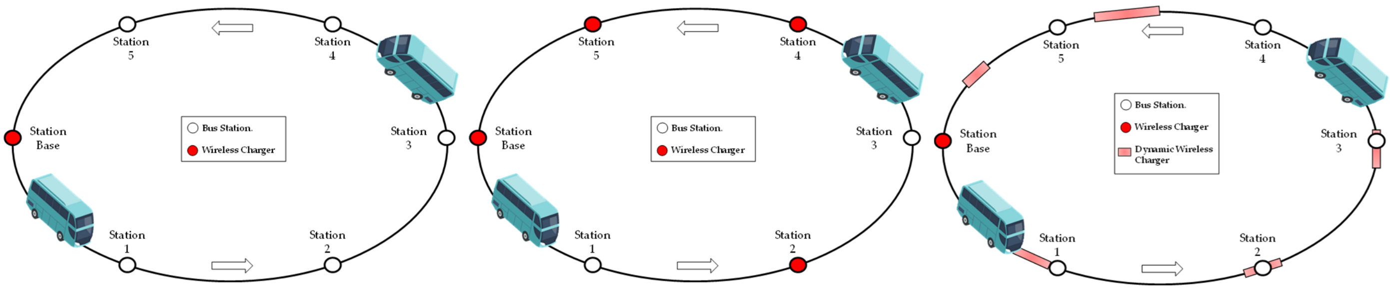
In public transportation system operations, there are three different types of wireless charging systems, to be specific, (a) stationary wireless charging (SWC), the charging only happens when the vehicle is parked or idle, (b) quasi-dynamic wireless charging (QWC), when a vehicle is moving slowly or in stop-and-go mode the power is transferred, and (c) dynamic wireless charging (DWC), the charging can be provided even when the vehicle is moving (Ulrich, 2012).

In New York City (NYC), the New York City Transit Authority (NYCTA) manages the most extensive public bus fleet in the United States, including 5710 public buses, serving over 764 million people per year, with 238 routes, with nearly 54,000 average weekday trips and 16,350 bus stops [6].

This paper compares the cost of the energy logistics for the three types of wireless charging networks (SWC, QWC, and DWC), using OLEV technology for a bus service transit in the borough of Manhattan (MN) (Figure 3) in NYC, where most of the trips are made, investigating bus routes to determine the optimum study area for planning out the costs of deploying a pilot service network.

The OLEV technology currently operates in several bus transits worldwide, including Seoul Grand Park and Gumi City transit lines in South Korea. There are three different categories of wireless charging systems (Figure 1) where OLEV can be used:

(a) stationary wireless charging (SWC),
(b) quasi-dynamic charging (QWC), and
(c) dynamic wireless charging (DWC).



(**a**) SWC-EV (**b**) QWC-EV (**c**) DWC-EV

Figure 1. Charging allocation properties for each type of EV [2].

SWC is only parked or idle charging, QWC is when a vehicle is moving slowly or is in stop-and-go mode, and DWC is supplied even when the vehicle is in motion. The cost and benefit of each system depends on various factors, such as route and fleet size, service range, battery prices, and installation cost [2,5].

OLEV technology has its sights set on economizing and sustaining the performance of industrial and commercial electric vehicles, with its current focus being bus transits. This is achieved by reducing the number of batteries required to operate the bus service, reducing the vehicle's cost and weight while always staying in service with its efficient, wireless charging technology.

The quantity of charging on each power track required for a DWC system is a function of vehicle speed and the elapsed time spent on that power track. In the conventional station allocation problem, the vehicle speed is not related to the allocation. Therefore, for optimum results, the system implementation should be in places where bus speeds are very low (bus stops, streets historically known for slow traffic). The median speed data, shown in Figure 3d is established on GPS bus data time, which indicates the location of individual buses over time on their routes. The data were collected between 4 p.m. and 6 p.m. every typical weekday in 2017 [7].

2. Literature Review

The public bus system helps to reduce traffic congestion and exhaust emissions [8]. However, due to vehicle technology limitations, diesel-powered buses still dominate today's bus fleet. Various regulations related to the problem of battery size, cost, and life of onboard batteries have restricted the popularity of electric buses [9].

Wireless charging technology is changing the form of energy transfer and utilization. Since its initial concept, suggested by Bolger et al. [10], significant technological achievements have been made in developing wireless charging. The development of wireless charging technology is surveyed by Wang et al. and Covic et al. [11,12]. To eliminate cables and dangerous sparking, wireless charging has been actively investigated in transit applications, such as charging, for electric vehicles [2].

Studies investigating how the charging strategy for e-buses interacted with the power grid [13] were based on charging infrastructure comparison [14,15], and the Battery Management Systems [9,16,17]. Ke et al. [18] proposed a model for simulating the operation and battery charging schedule of plug-in e-buses and determined the minimum construction cost of an all-plug-in electric bus transportation system. The OLEV system is the first successfully commercialized EV wireless charging system [19–21]. Related to wireless charging, Manshadi et al. [22] present the advantages of wireless charging stations, regarding electricity costs and congestion in the electricity network. Chen et al. [23] presents a charging-facility-choice model to explore the competitiveness of dynamic wireless charging by investigating EV driver's choice of charging facilities, between plug-in charging stations and charging lanes with dynamic wireless charging.

The OLEV consists of shuttles (similar to conventional EVs) and a charging infrastructure containing a set of energy transmitters that can charge the bus's battery remotely, utilizing an ingenious non-contact charging component while the buses are moving over the charging infrastructure. For the OLEV wireless charging system, Suh and Cho [24] explore two primary features: the power supply system and the pickup system. The former is installed beneath the road and wirelessly transmits the power; while the latter is attached to an EV and collects the power. The OLEV adopts a Shaped Magnetic Field in Resonance (SMFIR) technology, which effectively magnifies the electric waves Suh and Cho [25]. Finally, Suh and Cho [26], using an axiomatic design method, describes the detailed process of the system design matter and offer the process of defining the system-level functional requirements (FRs) and how the WPT system is designed to meet these system-level FRs.

The feasibility analysis and development of on-road charging solutions for future electric vehicles (FABRIC) was launched by the European Union to investigate the technological feasibility, economic viability, and socio-environmental sustainability of dynamic on-road charging EVs [27].

A feasibility study to investigate the dynamic Wireless power transfer WPT for EVs vehicles on England's major roads was published by the Transport Research Laboratory in the UK [28].

Cirimele et al. [29] describe a prototypal system for dynamic inductive power transmission in an overview of current state-of-the-art research and industrial projects. Similarly, Foote and Onar [30], review current high-power WPT systems and describe the passive elements, subsystems, devices, and techniques that have been developed to achieve high-power levels.

A Utah State University company, named Wireless Advanced Vehicle Electrification (WAVE), has been developing a project with two wireless charging transit buses, which are stationary and quasi-dynamic. A prototype was implemented as a campus shuttle (called Aggie Bus). It was equipped with a receiver and a transmitter embedded in the bus stops' pavement [31].

3. The Dataset

3.1. Dataset Description

Two different datasets were used for the analysis. The first one is the drive-type network data taken from the Open Street Map (OSM), using the OSMnx [32]. The second one consists of General Transit Feed Specification (GTFS), which defines a standard format for public transportation schedules and associated geographic information from the Metropolitan Transportation Authority (MTA) [33].

3.2. GTFS Data

The GTFS data feeds were collected from the Metropolitan Transportation Authority (MTA) to represent the MTA NYC bus routes and stops. The data package contains eight text files: Trips, stops, stop times, shapes, routes, calendar dates, calendar, and agency. Open-source Python 2.7.13, an interpreted object-oriented, high-level programming language, was used to visualize GTFS data, focusing on MN bus transit into Static Data Feeds (GTFS Schedule Data). Lines in this layer represent individual bus routes that follow the route's physical locations. They were generalized from the GTFS format, where lines depicted individual services. Please refer to Correa et al. [34] for more details on GTFS transit data. Figure 2 shows the number of buses from bus lines M1, M2, M3, M4, and M72 arriving at bus stop # 400,124 5 AV/E 72 ST by each hour.

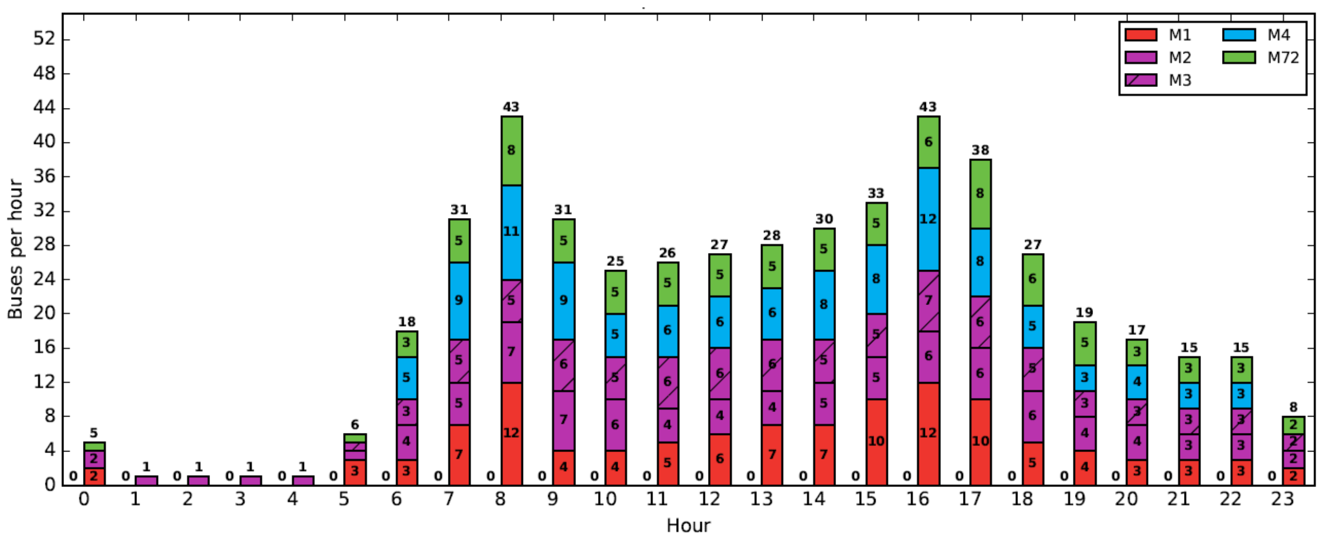


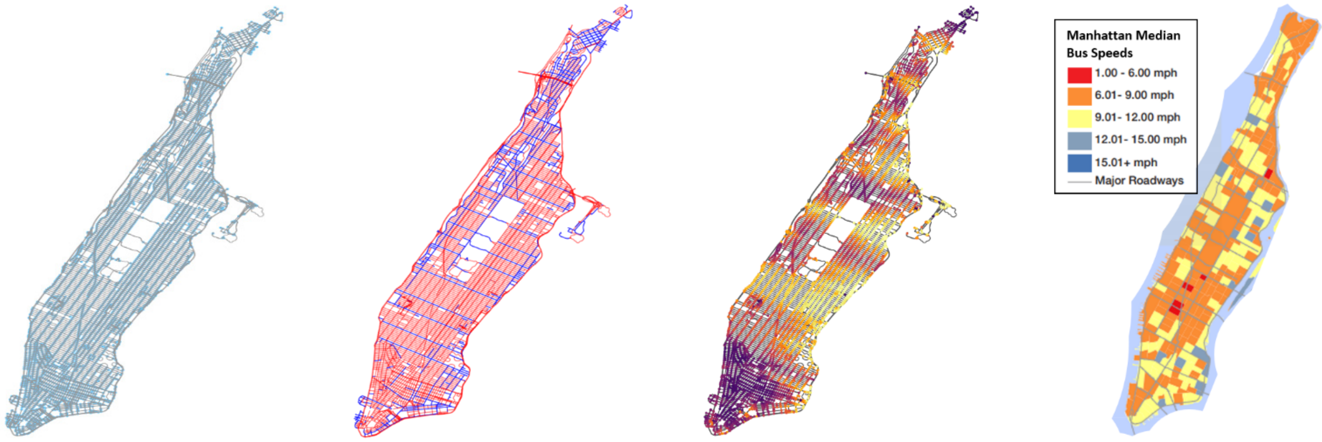
Figure 2. Visualization of GTFZ (Number of arriving buses to bus stop # 400,124 at 5 AV/E 72 ST).

3.3. GIS Data

Each line represents the route that a specific bus takes during regular weekday rush-hour service. The unique ID is route id, a field created by the MTA that uses the familiar letter or number designation for buses, with distinct ids for each bus route. It was created by the GIS Lab at the Newman Library at Baruch College CUNY as part of the NYC Mass Transit Spatial Layers series, so that members of the public could have access to well-documented and readily usable GIS layers of NYC mass transit features. This dataset is intended for researchers, policymakers, students, and educators for fundamental geographic analysis and mapping purposes.

3.4. Network Data

Drive-type network data from MN was taken from OSM using the OSMnx [32] to extract and clear the network. The network contains nodes for road intersections and joints, as shown in Figure 3. OSMnx downloads street network data that performs topological correction and simplification automatically to calculate accurate edges and nodes. The selected network types are "drive" to obtain drivable public streets and exclude service roads. (Figure 3a). OSMnx analyses networks and calculates network statistics, including spatial metrics based on geographic area or weighted by distance.



(**a**) (**b**) (**c**) (**d**)

Figure 3. Study area: Manhattan Borough in New York City. Network Data Visualization, (**a**) network contains nodes for road intersections and joints; (**b**) network provides the single way in red and double way in blue; (**c**) M22 bus network busiest nodes visualized from low (dark violet) to high (light yellow); (**d**) median bus Speeds of Manhattan.

OSMnx allows classifying one-way and bidirectional streets (Figure 3b). For one-way streets, directed edges are added from the origin node to the destination node. For two-way streets, reciprocal directed edges are counted in both directions between nodes. This ensures that intersections are not considered dead ends. OSMnx also allows identifying the busiest nodes through the network, as is shown in Figure 3c.

4. Materials and Methods

4.1. Route Selection

Based on the network and median bus speed information, we selected three MN bus routes located within the node's least busy area in MN in Figure 3c (dark violet colored), as the best option for actual potential implementation because it will produce less disruption in the city than other zones, such as midtown. In this project, information was collected from the Metropolitan Transportation Authority (MTA) data feeds for the NYC Manhattan Transit Bus transportation services. Initially, only three Manhattan bus routes: M8, M9, M22 (colored in green), were examined as the first analysis in the energy logistics (battery and charging infrastructure) cost for each system Figure 4.

(**a**) (**b**) (**c**)

Figure 4. Selected Routes. (**a**) M8 bus; (**b**) M9 bus; (**c**) M22 bus.

After data processing, we tested the accuracy of the data obtained from GTFZ feeds, comparing bus stops of each selected route to the real bus stops in the city, using google street view, as is shown in Figure 5. This method allows us to eliminate potential bias in the data collected.

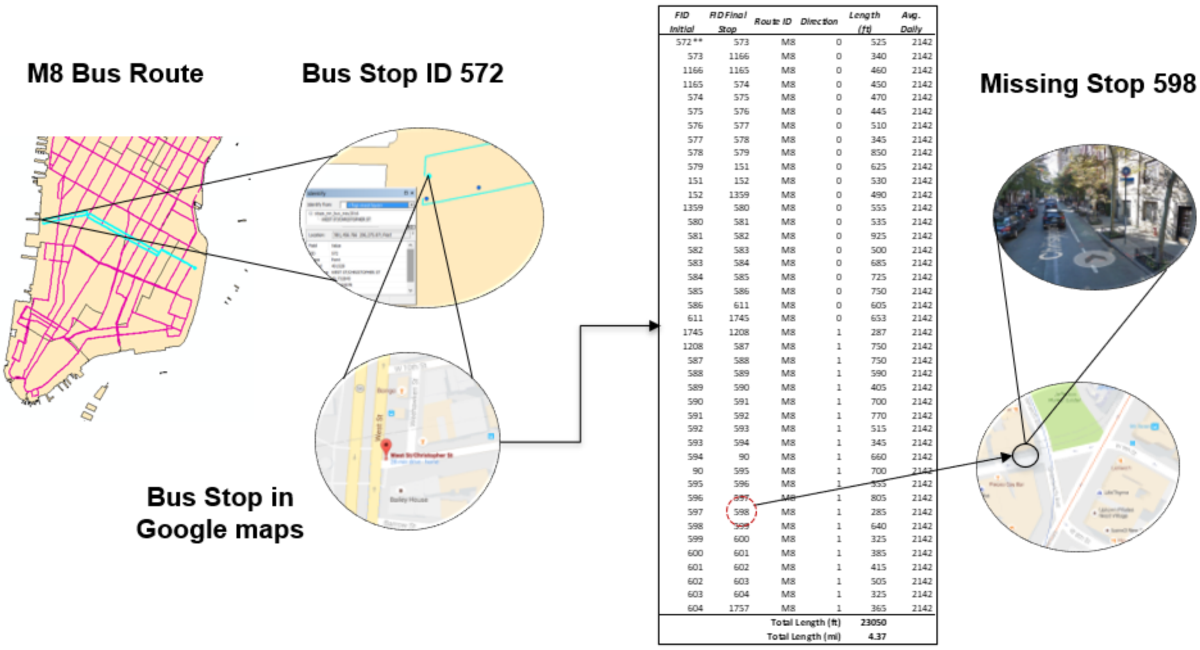


Figure 5. Comparison with real site data.

4.2. Economic System Design Method

For an EV-based transit system, the initial investment cost is fundamentally composed of two main components: the cost of the charging infrastructure and the cost of a fleet of vehicles. The cost is divided into the batteries' costs, the vehicle units, and the other charging components. The energy logistics cost accounts for the majority of the total cost of an EV-based transit system. Therefore, understanding the cost structure of energy logistics is critical for deciding on investments in EV-based transit systems.

Let us define Ts as the total energy logistics cost for one service route, operated with EVs of s type, and Φs, the cost function of energy storage in the vehicles for each type s Є{SWC, QWC, DWC}. Therefore, this cost is primarily determined by the size of the battery in the bus and the number of buses. Let Ωs be the cost function of energy transfer for each type s. Thus, this cost is mainly a function of the sum of the charging units. Then, the total energy logistics cost can be estimated as:

$$Ts = \Phi s(\text{batterysize}, \text{fleetsize}) + \Omega s\left(\sum_i \text{installationcostofchargingunit}i\right) \quad (1)$$

Our analysis tries to find the minimum cost evaluating Ts for each type, and we try to find the minimum cost of Ts while satisfying the service requirement. Specifically, the EVs operate with sufficient energy in their batteries to complete a service. Therefore, the minimum cost of Ts requires finding the least amount of investment needed for a service using each type of EV (min Ts, s. t. sufficient energy to complete a service).

In [2] (Jang et al., 2016), there is a qualitative cost-benefit analysis for each wireless system, depending on the battery price and infrastructure cost, as seen in Figure 6. However, investment in the OLEV cannot only be made based on such analysis. Therefore, reports from current OLEV and EV bus transit operations, MTA data feeds, and tools from GIS software were utilized to develop a method for comparing the energy logistics costs for these different types of charging systems on a chosen Manhattan bus route.

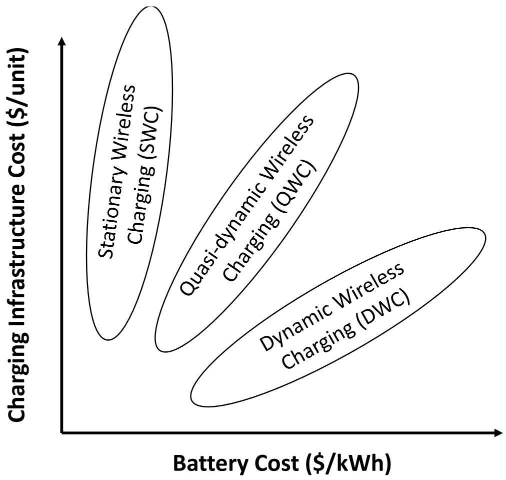


Figure 6. Qualitative analysis of the economic benefits of different EV charging systems [35].

Allocation of chargers for each system is that SWC should be installed only at the station (base) where the vehicles rest between services; QWC-identify where to install the wireless chargers at a minimum cost, based on energy consumption and depletion between stops in a route; DWC-, as the charging can be done while the vehicle is in motion, the vehicle speed should be considered determining the allocation of chargers along the route.

The optimization problem aims to minimize the energy logistics cost by finding the optimal decision variables. We define the minimum investment cost across the different types of EV as follows:

$$\text{SWC\&QWC} : \min[(No.Buses) * (Cost\ of\ KWh) * (Service\ Batery\ Size)\ ] + [(Cost\ of\ Charger)*(No.\ Chargers)] \quad (2)$$

$$\begin{aligned}\text{DWC} : \min[&(No.\ buses) * (Cost\ of\ KWh) * (Service\ Batery\ Size)\ ] + [(Power\ track\ cost\ per\ meter) * \\ &(Power\ track\ lenght) + (Cost\ of\ Charger) * (No.\ Power\ track\ units)]\end{aligned} \quad (3)$$

Once we determine the charging infrastructure's location and length, we can use Equations (2) and (3) to optimize the minimum energy logistics cost for SWC, QWC, and DWC systems. The cost of the battery per energy unit, charging unit, and power track per unit length can be found [34].

4.3. State of Charge Algorithm (SoC)

The implemented SoC algorithm inputs the initial model parameters (i.e., route's length, units of charge, time, the longitude of charge, type of battery, and battery's charge power) at the time zero state and returns how much energy is available for service based on battery size. Certain assumptions are needed, such as made-flat road, constant velocity, and one bus size, resulting in a continuous slope of energy consumption per length (kWh/km). Broadly, the algorithm uses iteration to solve how much available energy is left after one route trip. The algorithm terminates when the bus service ends and calculates how much remained energy is available for the next service, based on battery size, and the battery SOC is plotted. MATLAB programming is used to simulate the battery's state of charge (SoC) algorithm throughout a route to determine how well the allocation of charging units fit the model. The outline of the SoC algorithm is in Appendix A.

We assume that the average velocity of the bus is constant (4 mph) and the road grade is relatively level (0), which means that battery consumption will always have the same downward slope. Everything is a function of time, rather than displacement. The plot of the SoC simulation is shown in Figure 7.

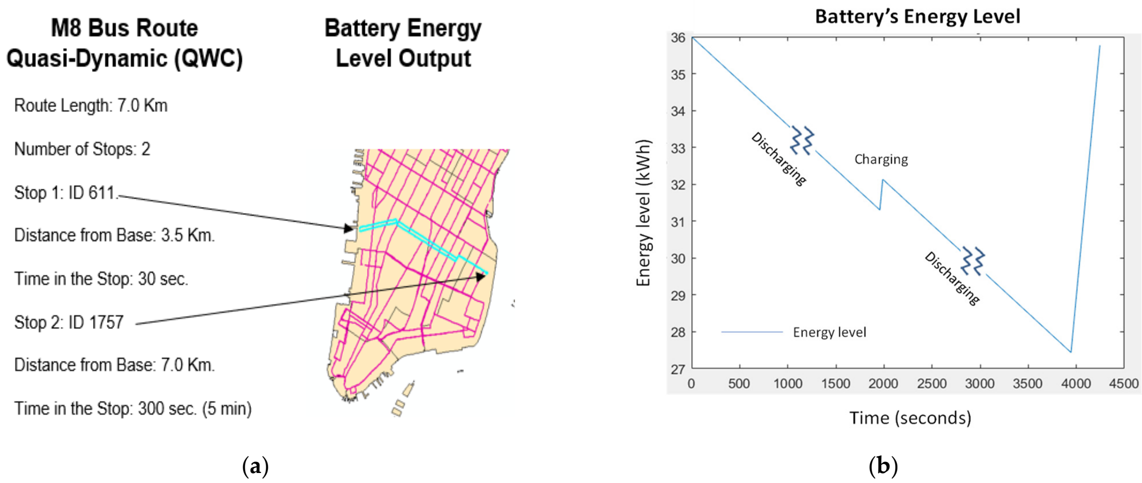


Figure 7. Simulation for Battery. (**a**) M8 bus details; (**b**) Simulation for Battery SoC.

A battery (capacity size of 60 kWh) simulation for the M8 bus route in Figure 7a is shown in Figure 7b. The energy level is within the upper and lower limits. We assume that the energy capacity of the battery is linearly proportional to the cost of the battery. This assumption is realistic, as an EV battery pack contains multiple battery cells, so the capacity is defined by the number of cells included in the battery pack. This method of linear cost calculation is also widely used in the industry.

The upper and lower boundaries of the battery (coefficients) are supplied by the battery's manufacturers (lower = 0.2 and upper = 0.8, respectively). The energy level should be within the lower and upper limits. In our analysis, the initial energy level is 36 kWh, as shown in Figure 7b. The input and output data for the displayed simulation are shown in Table 1**.**

Table 1. Input and Output of the SoC Algorithm.

Parameter	Value
Input	
Route length (Km.)	7
No. of changing units along the route (units)	2
Location of the charging unit No.1 (km)	3.5
Location of the charging unit No.2 (km)	7
Avg time spent at charging unit 1 (seconds)	30
Avg time spent at charging unit 2 (seconds)	300
Track charging power (kW)	100
Battery capacity, size (kWh)	60
Output	
Energy level-Lower limit (kWh)	12
Energy level-Lower limit (kWh)	48
Available battery capacity for service at time = 0 (kWh)	36
Available battery capacity after one service (kWh)	35.771

5. Results and Discussion

As shown in Table 2 and Figure 8, the data analysis conducted in this study evaluates the economic fleet size with the current cost structure for each system. Axis x and y represent the number of vehicles and the total investment cost for the M8 bus route. The entire cost of the system is proportional to the battery's full size (cost of SWC increases linearly). Beneath this assumption, the charger is installed only at the station base and is fixed, even if the number of Electric Vehicles grows. Thus, the energy logistics cost is linearly proportional to the fleet. In practice, more charging capacity would need to be added to the base station for the SWC system to avoid delays as buses wait to be charged, producing some non-linear discrepancies in the model. For the DWC case, the increment rate of cost is less significant than that for the case of SWC; for a DWC system, a growing number of EVs serves to improve the system. Therefore, smaller batteries are more economical. The rate of change in cost against the number of EVs decreases; hence the growing number of EVs improve the system.

Table 2. Cost Analysis of Wireless Network.

		Stationary (SWC)	
Route:	**M8 (42 Stops)**	**M9 (64 Stops)**	**M22 (44 Stops)**
Total Dist. in km	7.0	15.7	8.9
FID Stop Station	Base Station	Base Station	Base Station
Energy needed for service	140	140	140
Battery size (kWh)	233	233	233
No. of EVs	1.0	1.0	1.0
Battery cost per kWh	600	600	600
No. of chargers	1.0	1.0	1.0
Cost per charger	50,000	50,000	50,000
Length of Power Track			
No. of Power Tracks			
Power Track Cost (per m)			
	$190,000	**$190,000**	**$190,000**
		Quasi-Dynamic (QWC)	
Route:	**M8 (42 stops)**	**M9 (64 stops)**	**M22 (44 stops)**
Total Dist. in km	7.0	15.7	8.9
FID Stop Station	BS, 611, 1757	BS, 1720, 1769	BS, 1754, 1713
Energy needed for service	60	120	80
Battery size (kWh)	100	200	133
No. of EVs	1.0	1.0	1.0
Battery cost per kWh	600	600	600
No. of chargers	3.0	3.0	3.0
Cost per charger	50,000	50,000	50,000
Length of Power Track			
No. of Power Tracks			
Power Track Cost (per m)			
	$210,000	**$270,000**	**$230,000**
		Dynamic (DWC)	
Route:	**M8 (42 Stops)**	**M9 (64 Stops)**	**M22 (44 Stops)**
Total Dist. in km	7.0	15.7	8.9
FID Stop Station	BS, 611, 1757	BS, 1720, 1769	BS, 1754, 1713
Energy needed for service (2/3 of bat. size)	24	80	54
Battery size (kWh)	40	133	90
No. of EVs	1.0	2.0	2.0
Battery cost per kWh	600	600	600
No. of chargers	5.0	3.0	3.0
Cost per charger	50,000	50,000	50,000
Length of Power Track	500		
No. of Power Tracks	* 4		
Power Track Cost (per m)	600		
	$574,000	**$310,000**	**$258,000**
eff high	0.8		
eff low	0.2		

Note: Prices and equations for logistics cost was taken from: [2]; * x m at West/Christopher, y m at 9th/Broadway, z m at 8th/Mercer (4th charger @ Base Station).

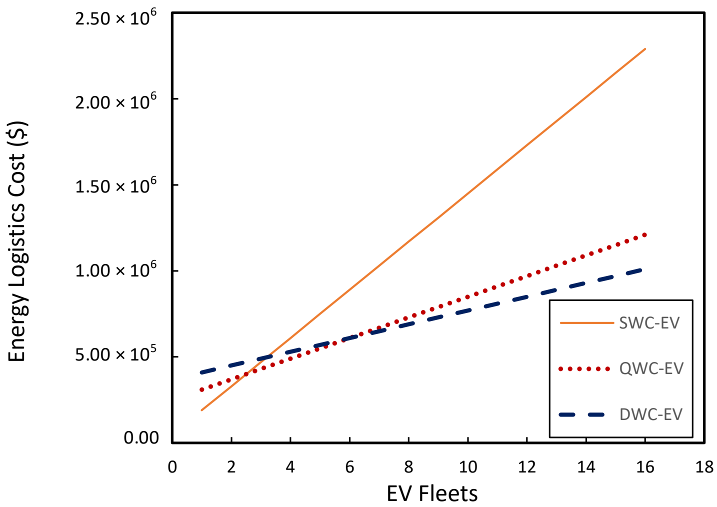


Figure 8. M8 Route Fleet-Scale Plot Analysis.

As shown in Figure 8, the cost lines for SWC-QWC and QWC-DWC cross when the number of vehicles is three and seven, respectively. This means that if there are less than three cars, SWC is the most economical and if the number of EVs is between three and seven, QWC is competitive. If the number of vehicles is more significant than seven, DWC is the most efficient and economical. The lines with lower costs SWC for fleet < 3, QWC for 3 < fleet < 7, and DWC for fleet > 7, regardless of the charging type, should be considered the lower bound for the wireless charging EV.

6. Conclusions and Future Work

Wireless charging technology offers the possibility of eliminating the last remaining cord connections required to replace portable electronic devices. This technology has significantly improved during the last decade and has led to a vast number of applications. In this article, we have investigated the implementation of wireless charging on bus routes in Manhattan, NYC, using OLEV technology, and developed a cost analysis of energy logistics for the three types of wireless charging networks: stationary wireless charging (SWC), quasi-dynamic wireless charging (QWC), and dynamic wireless charging (DWC). However, the method of analysis and approach, as well as the structure and logic of the model studied in this paper, is not limited to the KAIST OLEV system, and can be used for any charging system

In other words, the DWC system is helpful when the battery costs are high, but the costs of charging infrastructure are low. If the cost structure is the inverse, SWC is more beneficial. The cost–benefit outcome of a QWC system is somewhere between that of the DWC and SWC systems. The integration of wireless charging with existing transportation networks creates new opportunities, as well as challenges, for the development of sustainable cities. This study has shown the energy logistics cost analysis for the potential implementation of wireless power charging to an actual bus route in a congested area.

Different bus sizes and different road gradients may be added to make the model more practical. However, more data would need to be found to determine how the energy consumption (kWh/km) would correlate to these parameters. Given that wireless charging infrastructure is more expensive than the common plug-in chargers, only a limited wireless charging infrastructure (with short-scale service) might be economical.

In this paper, we provide only a qualitative analysis of different types of wireless charging. However, there is still lots of opportunity for improvement in our study and method. Thus, our research does not consider the number of SWC chargers needed as the number of EVs increases. Due to the queue waiting issue, more chargers should be required to support additional EVs. Traditional queuing theory can be used to determine the appropriate number of chargers for an SWC system. Another interesting study for future research is investigating the optimal speed profile because we use only a fixed constant velocity in the analyses and environmental impact analyses across various wireless charging systems.

This research could provide new possibilities for using OLEV technology, network, and bus route data to determine the optimum study area for planning out the costs of deploying a new electric bus service network. However, the implementation of power charging in networks is less explored and requires further investigation. Additionally, practical challenges in performing similar analyses of several NYC bus routes, based on the route's EVs history, ridership, and location, can be considered the main directions for future research.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

State of Charge Algorithm (SoC)

The outline of the SoC algorithm is shown in Figure A1, below.

Algorithm: Battery's State of Charge (SoC) simulation

```
% Load empirical data
{Route length, Time, Charge (km), Battery size, Charge power}
avg_dist_for_charge = route_len/charge_units
x = avg_dist_for_charge
for i = 1:length(timec) do
    charge_position(i) = x
    next_position = charge_position(i) + avg_dist_for_charge
    x = next_position
end for
%time spent, in seconds, to complete one service
one_service_time = round(route_len/ km_per_sec)
charging_time = 0;
for i=1: length(timec) do
    charging_time = round(charging_time + timec(i))
end for
total_service_time = one_service_time + charging_time
%create time array for plot
time = 0:1:total_service_time
% battery efficiency in kWk/mile for bus traveling at 4 mph
eff = 2.16 * (1/1.60934); % kWh/km
% convert efficiency to kWh/sec
eta = eff * km_per_sec ; % kWh/sec
charge_power_per_sec = charge_power / 3600 ; % kW/s
% loop to find at what times will the bus start charging
Set wait_time = 0
for i =1:length(charge_km) do
    times_for_charge(i) = round(charge_km(i)/km_per_sec) + wait_
    wait_time = wait_time + timec(i)
end for
% Calculate how much energy is available for service based on bat
eff_high =0.8;
eff_low =0.2;
energy_for_service = battery*(eff_high-eff_low)
% loop to create the state of charge plot
SoC = [energy_for_service]
Set index = 1
energy = energy_for_service
if times_for_charge =0 do
  charge = energy
  for i = index:total_service_time do
      soc(i) = charge - eta
      charge = soc(i)
  end for
  time = 1:1:total_service_time
  % create SoC plot
  plot(time,soc)
else
   for i =1:length(times_for_charge) do
      charge = energy
      % battery drain
      for k = index:times_for_charge(i) do
         soc(k) = charge - eta
         SoC(end+1) = soc(k)
         charge = soc(k)
         index = times_for_charge(i)
      end for
      %battery charge
      for j=1:timec(i) do
         SOC(j) = charge + charge_power_per_sec
         SoC(end+1) = SOC(j)
         charge = SOC(j)
      end for
      index = index + timec(i)+1
      energy = charge
   end for
   % create SOC plot
   plot(time,SoC)
end if
```

Figure A1. Algorithm to run the State of Charge (SoC).

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