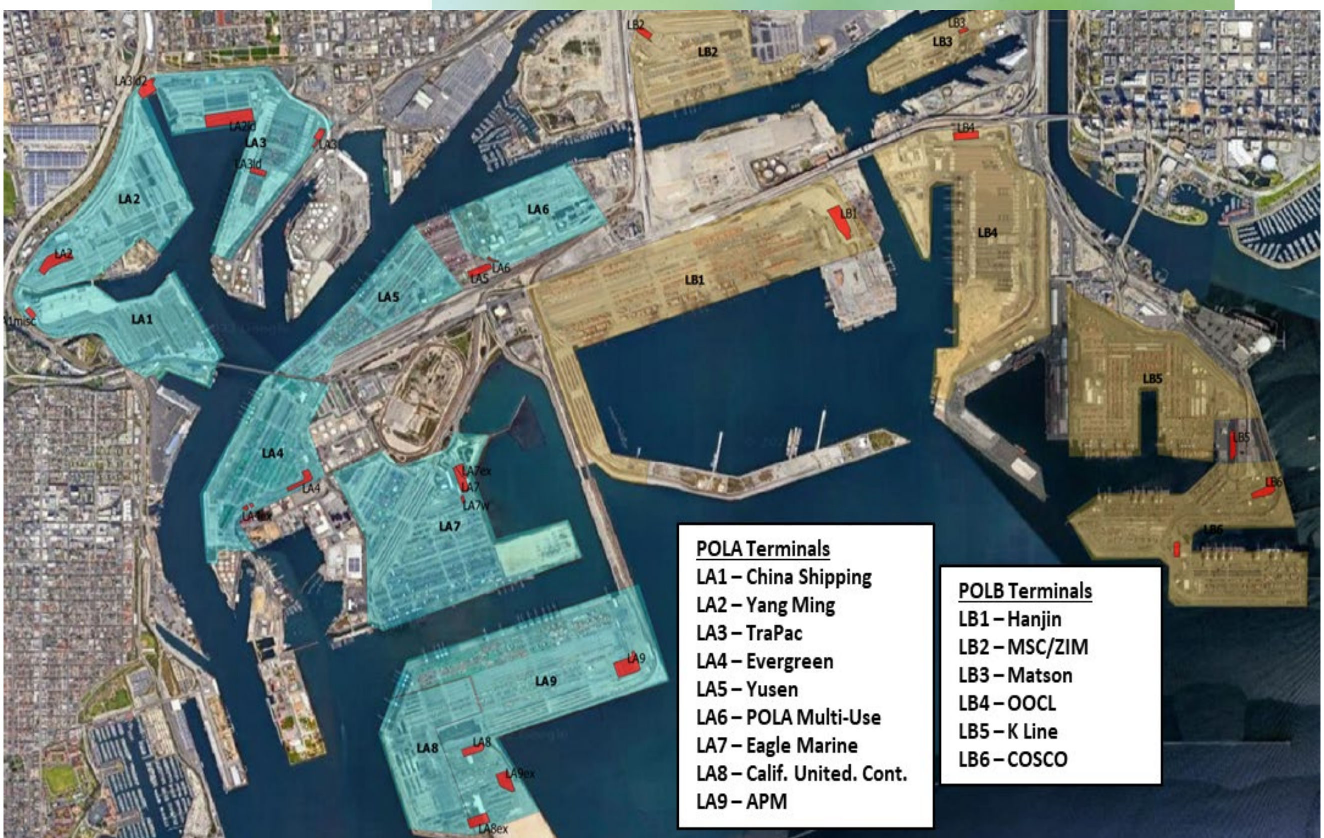
ASSESSING ROLES OF INDUCTIVE OPPORTUNITY CHARGING IN BATTERY ELECTRIC TRUCK OPERATIONS BASED ON REAL-WORLD TRUCK ACTIVITY DATA



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16. Abstract Class-8 battery electric trucks (BETs) were modeled and simulated in this project to determine their capability in fulfilling real-world drayage activity under different operational scenarios. Two different cases were developed and studied: (a) inductive or wireless charging at port terminals, and (b) wireless charging at loading/unloading stops. For port terminals, potential wireless charging zones were identified, and wireless charging opportunities were introduced to improve drayage activity fulfillment of BETs. The results showed that current BETs could fulfill approximately 79–86 percent of the real-world drayage activity sample used in this research and that their ability to receive wireless opportunity charging at port terminals could help increase the activity fulfillment to about 84–91 percent. For loading/unloading stops, energy gains from wireless charging for two trucks with 50 and 150 kW charging powers were studied. The results from this case study showed that one of these trucks needed opportunity charging at the home base once for the studied two-day period. The other truck needed additional opportunity charging at stops and would have benefitted from tour rescheduling to allow an extension of the stop duration to increase the charging duration.			
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Executive Summary

Problem Statement

This report addresses the challenges posed by the limited range of battery electric trucks (BETs), particularly in the context of drayage operations. Drayage trucks typically operate short trips between ports, railyards, and warehouses, often returning to their base multiple times a day. Although BETs are deemed to be suitable for such operations due to their limited daily mileage and high energy efficiency in stop-and-go traffic, concerns remain about the availability and efficiency of charging infrastructure. BET fleets face operational constraints when opportunities for recharging are limited, particularly during periods of high demand or when trucks spend little time at the base. This report investigates the role of inductive (i.e., wireless) opportunity charging in extending the range and operational feasibility of BETs in real-world drayage operations.

Technical Objectives

The primary goal of this research was to explore the viability of inductive opportunity charging to extend the operational range of BETs in drayage operations. The project focused on two specific case studies:

1. Inductive Charging at Port Terminal Gates: This case study analyzed the potential benefits of installing wireless charging infrastructure at port locations where drayage trucks typically spend time waiting or queuing.

2. Inductive Charging at Loading/Unloading Stops: This case study explored the feasibility of wireless charging at non-port locations, such as warehouses, where trucks stop to load or unload cargo.

The research aimed to determine:

- How wireless charging could help meet the energy demands of BETs during drayage operations.

- The effectiveness of different wireless charging power levels and their ability to extend truck range.

- The potential for reducing operational downtime by eliminating the need to travel to charging stations.

Key Findings

- Operational Feasibility of BETs: BETs with current battery capacities (377 kWh and 565 kWh) can feasibly complete 80–86% of drayage tours under base charging conditions. When wireless charging is added at port locations, up to 90% of tours can be completed.

- Charging Efficiency and Power Levels: The study found that wireless charging power levels of up to 500 kW significantly improve the range and tour completion of BETs. However, gains beyond 250 kW are minimal for smaller batteries, as higher power levels benefit larger battery capacities more effectively.

- Impact of Charging Location: Wireless charging at strategic locations where trucks spend the most time idling or queuing, such as at port terminal gates or warehouse loading docks, offers an advantage as it eliminates the need for additional trips or time spent traveling to charging stations.

Project Impacts

The findings from this research support the adoption of inductive opportunity charging as a means to extend the range of BETs without impacting operational efficiency. By strategically placing wireless chargers at key locations, such as ports and warehouses, fleet operators can maximize the use of BETs while reducing emissions and meeting environmental goals, particularly in regions such as Southern California, where drayage operations occur near minority and low-income communities. In addition, wireless opportunity charging can help reducing operational costs, as it eliminates the need for additional trips or time spent traveling to charging stations.

The installation of wireless chargers at ports and warehouses can significantly enhance the viability of BET fleets. However, careful planning is required to ensure chargers are placed in optimal locations where trucks spend the most time idling. Future work should focus on developing an optimal strategy for prioritizing wireless charging zones based on truck activity data. Additionally, more research is needed to explore the impact of higher power chargers and the potential for reshuffling tour schedules to further improve BET fleet performance.

Acknowledgments

This study was funded by a grant from the Center for Advancing Research in Transportation Emissions, Energy, and Health (CARTEEH), supported by the U.S. Department of Transportation (USDOT) through the University Transportation Centers program. The authors would like to thank the CARTEEH and the USDOT for the funding provided in support of this project. The authors would also like to thank the drayage operator who allowed data collection on the trucks.

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Introduction

One of the major frontiers for transportation emission reduction is the electrification of heavy-duty trucks. Due to the higher energy requirement of these vehicles compared to passenger cars, the capabilities of battery electric trucks (BETs) have long been questioned. With recent advances in battery technology and electric vehicles (EVs) in general, longer-range EVs are becoming more mainstream. Ever-faster charging is also becoming available. However, even though battery electric Class-8 trucks are currently available commercially (*1*), with more poised to enter the market in the near future (*2*), concerns regarding the range and charging requirements of heavy-duty BETs still remain. Such concerns are valid for long-haul applications, but shorter-distance operations such as drayage appear suitable for BETs that are available in the current market with advertised ranges of longer than 250 miles (e.g., (*1*)). *Drayage* is defined as the activity of transporting containers and bulk in between ports, intermodal railyards, and nearby warehouses by heavy-duty trucks (*3*). Drayage trucks typically work out of a base, return to the base at least once per day, have limited daily mileage, and spend large portions of driving time in transient modes or creeping. These are all prime characteristics that make drayage trucks suitable for electrification since (a) the frequent base visits can be used for charging, (b) the limited mileage addresses the range anxiety, and (c) the frequent braking and slow-speed movement favor BETs over diesel trucks due to regeneration and reduced energy consumption. Moreover, in Southern California, drayage truck activities primarily take place near minority and low-income communities, raising environmental justice concerns (*4*). Therefore, at least on paper, BETs present a strong case to replace diesel trucks in drayage fleets.

However, failing to sufficiently recharge the batteries is a major concern for some drayage fleets whose trucks spend little time at base in between tours. Tanvir et al.'s analysis showed that a fleet of BETs with a 250 kWh battery could perform 75 percent of the tours if base charging between tours was considered (*4*). In this project, inductive opportunity charging as a means to extend BET range has been explored for two different cases. *Opportunity charging* can be understood as any opportunity that the EV has to charge its battery, including brief stops at traffic intersections or stops to load or unload passengers at a bus station (*5*, *6*).

The first case study of this project investigated if inductive charging (also known as wireless charging) at port locations where drayage trucks spend considerable amounts of time can help to increase the proportion of tours that are feasible. Installing wireless chargers at ports can benefit both drayage operators and the port authority (*7*). The operators benefit from out-of-base accessible charging opportunities that require no extra travel (driving to and from charging station) and labor (connect-disconnect charging port), without bearing any installation and maintenance overhead. Availability of out-of-base charging stations for BETs can be uncertain and insufficient, which causes concerns when scheduling the tours. Wireless charging mitigates this issue as well. The port authority benefits from the operators opting to increase BET penetration in fleets, thereby reducing emissions and thus meeting port objectives (*8*).

The second case study investigated en-route inductive opportunity charging at loading/unloading stops regardless of them being port locations or not. This case study utilized a different dataset than the first one and conducted its own scenario development and analysis. Wireless charging at places where trucks usually stop for loading/unloading can be more convenient than traditional wired charging since it negates the need for plugging in and removing the cable before leaving every time. Loading docks can also be congested and inconvenient locations for traditional charging stations and places to plug in trucks.

Using this two-pronged analysis, this project contributes through its simulation of current BETs for drayage application, identification of wireless charging zones at port terminals, and study of the effect of inductive opportunity charging on BET drayage operation.

Literature Review

Wireless power transfer (WPT) developments started back in 1897, with Nikola Tesla experimenting with the transmission of electrical energy without wires in Colorado (*9*). Developments of this technology continued through the years. In 1976, dynamic WPT was first introduced by the Lawrence Berkeley National Laboratory; in 1993, the University of Auckland patented a non-contact power distribution system; in 2007, the Massachusetts Institute of Technology proposed a mid-range WPT technology using magnetic resonance (*9*); and in 2009, dynamic wireless charging of EVs demonstrating the feasibility of dynamic WPT (*10*) was developed by the Korea Advanced Institute for Science and Technology (KAIST). Developments continued in 2010 in Germany, with a combination of static and dynamic charging systems for trams, and in 2013, Oak Ridge National Laboratory (ORNL) also investigated an in-motion WPT system for EVs (*10*).

WPT can be classified into three main technologies, as shown in Figure 1: electromagnetic induction (also called magnetic coupling [*10*]), electrostatic induction (also called electric coupling or capacitive power transmission [*10*]), and electromagnetic radiation (*11*). Long-distance wireless power charging can be achieved by using electromagnetic radiation in the form of a microwave or laser. One of the most common applications of this technology is the transmission between solar power satellites and the earth (*6*). However, this mode is not only inefficient, it can even be harmful because of the omnidirectional characteristic of radiative energy in the far field (*10*). Electromagnetic and electrostatic induction are considered near field and nonradiative. In electrostatic induction, there is an electric field between the metal plate electrodes used to transmit the energy. This type of WPT has not been studied as extensively as electromagnetic induction, mostly because electric fields are more hazardous to living things than magnetic fields (*10*). Finally, electromagnetic induction works on the principles of a magnetic field and can be divided into inductive coupling (also known as inductive power transfer [IPT] [*10*]) and strongly coupled magnetic resonance (also known as coupled magnetic resonance system [CMRS] [*10*]). IPT is one of the most used methods in WPT applications to charge EV batteries. In IPT technology, the secondary coil is usually on the bottom of the vehicle, while the primary coil is often buried at the charging ground. When the coils are aligned and the primary coil is energized, a magnetic field is established that produces a current in the secondary coil (*11*). Finally, CMRS is considered just a special and optimized case of IPT with a longer wireless power transmission (*10*).

In recent years, WPT has been labeled as a technology that provides new opportunities for EVs that enhance a more sustainable mobility by taking advantage of “opportunity charges” and by downsizing the battery (*6*). Opportunity charging can be understood as any opportunity that the EV has to charge its battery, including brief stops at traffic intersections or stops to load or unload passengers at a bus station (*5*, *6*). A case study on a light-duty EV from the University of Toronto showed that depending on the extent of the opportunity charging (ranging from 15 to 25 seconds), a battery size reduction from 6 to 85 percent is possible, and also a range extension between 7 and 600 percent is realizable (*5*). In addition, when using WPT technologies, some studies from the University of Michigan and applications from KAIST have shown that the EV battery can be downsized by at least two-thirds (*12*, *13*). Moreover, Bi et al. (*12*) also mentioned that WPT systems consume 0.3 percent less energy and emit 0.5 percent less greenhouse gases in the total life cycle than plug-in charging systems. Although WPT presents many benefits related to battery size and fuel economy improvements, the main concerns are still economic feasibility and charging efficiency (*6*).

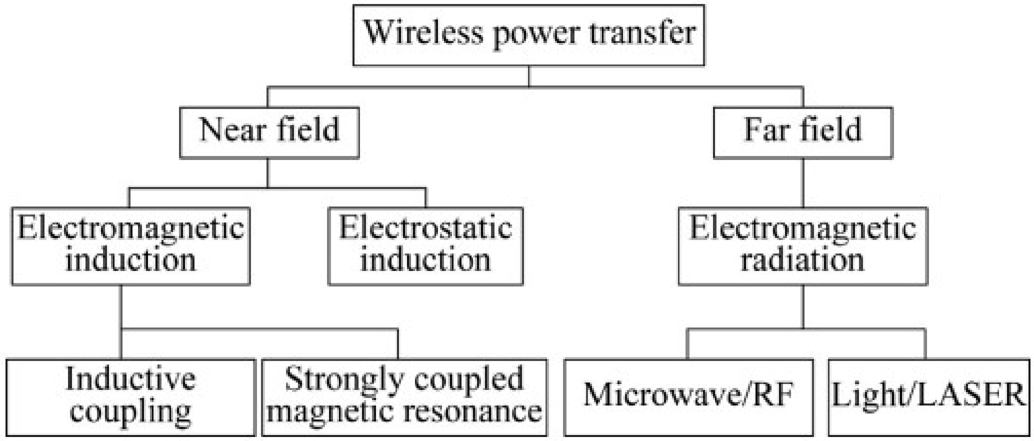


Figure 1. WPT methods (*11*).

Table 1 summarizes systems parameters, including efficiency, of some stationary and dynamic wireless charging systems using electromagnetic induction. In 2012, Utah State University built an advanced test facility for dynamic wireless charging as a way to study how this technology will allow an unlimited range extension for passenger EVs (*6*). In addition, ORNL partnered with the National Renewable Energy Laboratory and the Idaho National Laboratory to perform a feasibility study of dynamic wireless charging on traffic data from passenger EVs in Atlanta. In Europe, another feasibility study called FABRIC that used wireless charging on passenger cars was conducted from 2014 to 2017. The goal was to study the development of on-road charging solutions and large scale deployment of electromobility for future EVs (*6*). It is important to mention that some inconsistencies have been found in the literature in terms of efficiency measurement. Some studies used the AC grid to battery pack efficiency, whereas others used the DC input to battery pack efficiency. According to Bi et al. (*6*), it is preferable to know the AC grid when determining battery pack efficiency since it is directly related to the energy consumption. Overall, dynamic charging systems present a lower efficiency than static wireless charging systems, mainly because part of the magnetic flux generated by the primary coil is not coupled with the secondary coil, thus resulting in a decrease on energy received, especially at high speeds.

Table 1. Summary of System Parameters Related to Electromagnetic Induction WPT (*6*)

Institute	WPT	Power (kW)	Air Gap (mm)	Efficiency (%)	Year
Utah State University	Static	5	175–265	90[a]	2012
Saitama University, Japan	Static	3	200	90[b]	2012
University of Auckland	Static	1	100	91.3[c]	2015
University of Michigan-Dearborn	Static	7.7	200	96[b]	2014
	Static	6	150	95.3[b]	2015
ETH Zurich, Switzerland	Static	5	52	96.5[b]	2015
KAIST, Korea	Dynamic	3–25	10–200	72–83[a]	2009
Oak Ridge National Laboratory	Dynamic	1.5	100	75[b]	2013
North Carolina State University	Dynamic	0.3	170	77–82[b]	2014

Note: Usually, the efficiency is higher for static WPT at higher output power levels, and efficiencies are also higher when comparing static vs. dynamic charging systems.
[a] AC grid to battery pack efficiency.
[b] DC input to battery pack efficiency.
[c] Coil efficiency.

In addition, some examples of real-world applications of WPT technologies applied to urban electric transit buses are presented in Table 2. Most of the developments have been applied to urban electric transit buses because of their fixed route schedule. According to the Chattanooga Area Regional Transportation Authority (CARTA), a short opportunity charge of 1 minute at 60 kW can extend the range of an electric bus by approximately 1 mile. The KAIST On-Line Electric Vehicle (OLEV) project in South Korea allows buses to charge EVs while either stationary or in motion. This project started in 2009 in Gumi City, and it allowed operators to downsize the battery to less than one-fifth of a normal conductively charged battery. In addition, the state of charge (SOC) of the buses in this project can be kept in the range of 40–60 percent in contrast to the 20–90 percent in a normal charge, thereby extending the battery life (*6*).

Table 2. Summary of Wireless Charging Electric Bus Projects (*6*)

Project	Start Year	Location	Efficiency (%)
Bus project in Italy	2003	Turin, Italy	90[b]
KAIST-OLEV	2009	South Korea	72-83[a]
Bombardier PRIMOVE IPT	2010	Germany-Belgium	>90[a]
CARTA	2011	TN, USA	90[a]
WAVE	2012	UT, CA, TX, MD, USA	90[b]
ZTE Corporation Projects	2014	China	90[a]

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

Wireless charging on buses and passenger cars are just a few applications of WPT technology. Wireless power charging can be applied to any transportation mode that has a fixed route operation, such as the ones found in airports, harbors, rail systems, etc., and in fact, good candidates for wireless charging are drayage trucks. Usually, they carry cargo containers from shipping ports to nearby distribution zones, and they also return to home base daily during operation (*4*, *6*). Several researchers have identified the activity pattern of drayage operations and highlighted these trucks as some of the best candidates for electrification. Ambrose and Jaller (*14*) found in analyzed truck trips that less than 1 percent of drayage trucks completed more than five trips per shift, and on average a truck delivered 12 round trips per day. The study also mentioned that the trucks spend most of their time navigating the port and dealing with cargo logistics (port access, loading, etc.), while completing about 60 miles per day near-dock service (*14*). In addition, drayage fleet efficiency has also been studied. In Namboothiri and Erera (*15*), a drayage operation planning approach that minimizes cost and maximizes productivity was presented to deal with port access restrictions by slot capacity availability. Results showed that drayage activity productivity can be increased by 10–24 percent when port access capacity is increased by 30 percent (*15*). Furthermore, drayage truck emissions have also been assessed over the years. In Schulte et al. (*16*), a coordinated truck model was presented to reduce emissions from empty truck trips. Their results suggest that a collaborative truck appointment system is an effective tool to reduce emissions, but a congestion management tool is also needed at ports (*16*).

Over the years, several studies have targeted zero-emission drayage operations in Southern California. In 2012, a report prepared by Gladstein for the South Coast Air Quality Management District highlighted the potential benefits of catenary-accessible hybrid trucks in the port of Los Angeles (POLA) (*17*). The report also mentioned how this plan could also be applied to other ports, such as New York, New Jersey, Houston, Charleston, Seattle, Oakland, and Vancouver. Developments moved forward, and in 2017, Siemens built a test eHighway in Carson, California, near the port of Long Beach (POLB). The system only had three freight trucks that paired with the one-mile-long catenary system: a BET, a natural gas hybrid-electric truck, and a diesel-hybrid truck. The BET and natural gas truck were developed by a company called TransPower, and the diesel-hybrid truck was developed by Volvo-owned Mack Trucks. The trucks released zero emissions when connected to the catenary, and when the eHighway ended, the trucks returned to using their internal engine to drive the rest of the path (*18*). In 2013, a study from CALSTART aimed to research, identify, and evaluate potential technologies to address drayage needs while achieving zero emissions in the San Pedro Bay Ports (*19*). This research was intended to specify the requirements that zero-emission trucks must meet in order to substitute for conventional diesel trucks and emphasized the importance of routing strategies to improve productivity (*19*). In addition, a report from the Luskin Center for Innovation at the University of California Los Angeles (UCLA) released in October 2019 examined the barriers and opportunities of zero-emission drayage trucks. The authors described the importance of an accelerated transition to a zero-emission truck fleet to achieve the 2035 zero emissions goal, stressing that the volume of containers going through the ports is projected to increase over time. Moreover, freight truck miles traveled are estimated to increase by 80 percent from 2008 levels by 2035 (*20*). The authors also mentioned the importance of installing charging equipment to fuel BET and the challenges of charging times that require trucks to remain stationary for extended periods of time (*20*). Those situations are when wireless opportunity charging could play a leading role in accelerating this transition, especially in the San Pedro Bay Ports (*21*).

There are still some questions that need to be answered. The most important ones are whether electric trucks are capable of meeting the needs of drayage operations at the fleet level, and how are these trucks going to be charged to minimize emissions (*22*). A summary of causes, costs, and implications of heavy-duty vehicles' depot charging is presented in Borlaug et al. (*22*). They modeled depot-charging load profiles for multiple scenarios that considered fleet size and charging strategies. The authors concluded that the opportunity for a managed depot charging of heavy-duty trucks depends on their duty cycles, and there is a high variance in fleet electrification outcomes depending on fleet vocation and grid conditions (*22*). In Tanvir et al. (*4*), activity of drayage trucks in Southern California was analyzed to estimate the corresponding electric energy consumption and SOC of the battery. Their results showed that 85 percent of the tours could be served by electric trucks if there is opportunity charging at the home base during tours. Moreover, opportunity dynamic wireless charging has also been studied in (*23*, *24*). In Hwang et al. (*23*), an optimal dynamic wireless charging system design that minimizes installation cost while maintaining operational feasibility was proposed. In Deflorio and Castello (*24*), an electric charging scenario applied to cargo trucks was simulated, taking into account traffic and energy dynamics. Their method was able to measure the impact on dynamic wireless charging from traffic delay, energy requirements, and speed (*24*).

Case Study I: Inductive Charging at Port Terminal Gates

Methodology

Data Collection

This study used vehicle activity data collected from 20 Class-8 diesel trucks operating out of the fleet base located about a mile away from the Los Angeles port. The fleet primarily served the San Pedro Bay port complex (POLA and POLB), the Greater Los Angeles Metropolitan area, and the Inland Empire area. Occasionally, the fleet also serviced destinations in Central Valley and inland Northern California. Over 170 engine control unit parameters and global positioning system (GPS) data (e.g., timestamp, speed, longitude, latitude) were recorded at 1 Hz with data loggers. The collected data were then processed in multiple steps for data cleaning and correction, identifying trips, and trip origin-destination cloaking for confidentiality (*25*). Road grade data were added through map-matching. Only the freeway grades were available; thus, for non-freeway portions of the trips, road grade was considered 0 (flat terrain). The final dataset provided truck activity for the week of Monday, January 23, 2017, through Friday, January 27, 2017.

Tractive Energy Consumption Model

Using the 1 Hz activity data, the tractive power requirement for BET at each second, P_t, was calculated as:

$$P_t = m v_t a_t + 0.5 \rho C_d A v_t^3 + C_{rr} g m v_t cos\theta + g m v_t sin\theta \quad (1)$$

where m is BET mass, v_t is instantaneous speed, a_t is instantaneous acceleration, ρ is air density, C_d is coefficient of drag, A is BET front area, C_{rr} is coefficient of rolling resistance of BET tires, g is gravity, and θ is angle of inclination of the road. The collected data did not record instantaneous mass; thus, a static BET (plus cargo) mass of 35,906 kg was used (*4*).

Instantaneous energy consumption, $E_t^{Consumed}$, from the battery can be obtained by considering the component efficiencies:

$$E_t^{Consumed} = P_t / \eta_W \eta_{Fd} \eta_M \eta_B \quad (2)$$

where $\eta_W, \eta_{Fd}, \eta_M,$ and η_B are efficiencies of wheel, final drive, motor, and battery, respectively. η_B was calibrated to match the rated range of the simulated BET (275 miles with a 565 kWh battery [*1*] and weighing 80,000 lb).

Negative P_t instances (deceleration) at certain thresholds of speed and acceleration provided regeneration (*26*):

$$E_t^{Regen} = P_t \eta_W \eta_{Fd} \eta_M \eta_B ;\ \forall (P_t < 0) \cap (v_t > 5) \cap (a_t < 3) \quad (3)$$

Wireless Charging Model

The BETs were assumed to charge wirelessly at out-of-base locations wherever wireless chargers were available. Placement of wireless chargers needs to be strategic to maximize their utilization. In this study, zones at the San Pedro Bay port complex where drayage trucks spend a significant amount of time stopping or queuing (e.g., terminal gates) were considered for this purpose since it would allow the trucks the most opportunity for charging. To identify these locations, different terminals at the port complex were identified first (Figure 2). Collected truck activity data were then used to estimate stop/queuing time within terminal boundaries. Potential wireless charging zones were selected from locations in the terminals with a cluster of stop/queuing data points. To do so, vehicle activity data were filtered first by speed (speed = 0) to find where the trucks were stopping/idling. These data points, paired with aerial images, aided in estimating queuing areas; polygons drawn around them then gave potential wireless charging zones. Next, by geofencing, the collected GPS data were used to identify instances of truck presence at any of the potential charging zones. Noisy GPS data showing a position change when vehicles were not moving were corrected. This step was done by considering a vehicle staying in a charging zone when its speed is zero even though GPS data show it moving out of the zone. Consecutive matched geofence data points were finally grouped together to create potential charging events, as if wireless chargers were installed in those zones. The summary of such events identified for each truck is shown in Figure 3. During wireless charging, instantaneous energy gain was calculated as:

$$E_t^{WirelessCharge} = \begin{cases} P_{WC}\eta_{WC}; \text{if truck in charging zone} \\ 0; \text{else} \end{cases} \quad (4)$$

where P_{WC} is wireless charging power, and η_{WC} is wireless charging efficiency.

Instantaneous battery energy consumption can now be calculated as:

$$E_t^{Battery} = E_t^{Consumed} + E_t^{Acc} - E_t^{Regen} - E_t^{WirelessCharge} \quad (5)$$

where E_t^{Acc} is the per-second energy consumption of accessory loads (e.g., air conditioning); here, it is the same as the accessory load rating, P_{Acc}. Now, the total battery energy consumption in a trip can be found by:

$$E_{trip}^{Battery} = \int_{t=1}^{t=T} E_t^{Battery} ; T = \text{trip duration} \quad (6)$$

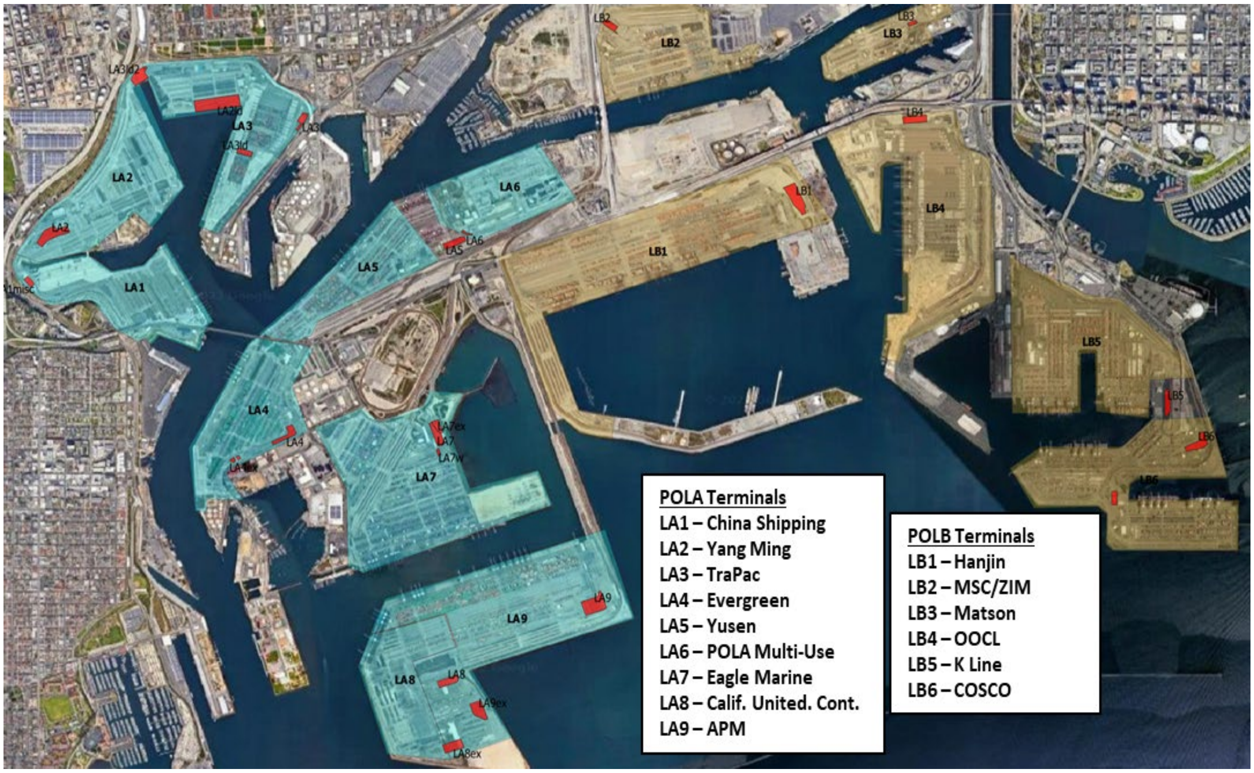


Figure 2. Locations identified to place wireless chargers (in red) at different terminals (marked by translucent turquoise and brown polygons) at the POLA and the POLB.

Operating hours	36	55	84	68	68	37	59	64	74	53	41	75	34	70	64	76	*958*
Operating seconds	128397	197437	302426	246244	245843	133106	211466	230303	268009	190459	147875	270473	121164	252249	231706	273295	*3450452*
Zone/Truck ID	**LL052**	**LL056**	**PEN016**	**TEC004**	**TEC006**	**TEC025**	**TEC039**	**TEC042**	**TEC043**	**TEC044**	**TEC045**	**TEC046**	**TEC047**	**TEC048**	**TEC049**	**TEC050**	***Sum***
LB6	550	194	0	253	0	0	3567	1406	64	1911	1013	0	99	0	0	0	*9057*
LB6misc	229	0	0	6	0	0	917	0	1532	0	1088	0	0	721	0	0	*4493*
LA5	3	2187	5285	0	0	0	0	0	0	3982	611	0	397	0	0	164	*12629*
LA9	4790	0	3122	0	7933	12574	7770	0	6252	2763	3021	7649	9070	4324	7273	4574	*81115*
LA8ex	95	0	642	0	647	286	3789	0	1778	179	559	818	5068	1147	1112	550	*16670*
LA9ex	183	0	416	0	564	4191	3633	0	1754	143	760	442	1925	1037	378	825	*16251*
LA4ex	160	30	22	0	651	831	81	639	13	207	108	244	0	1604	234	563	*5387*
LA4ex2	235	331	62	0	269	211	80	545	161	299	179	136	0	263	1231	835	*4837*
LA4	481	1207	273	0	2619	998	320	7737	2432	5653	576	2952	0	5884	1271	10210	*42613*
LA7ex	755	1348	4309	2157	1718	236	1867	1169	1177	1667	103	3232	15	2889	2456	1422	*26520*
LA3ld2	5099	2382	3579	10449	7760	442	0	5147	5180	538	0	3768	121	413	1891	1164	*47933*
LA7	2445	1977	6072	15733	10665	4338	4545	3381	16474	9655	145	26322	441	12674	3483	12766	*131116*
LA3	1732	61	6402	180	184	51	0	288	823	39	6	34	0	207	0	0	*10007*
LA3ld	324	174	2354	997	1755	724	0	318	0	153	0	650	0	199	0	0	*7648*
LA2ld	182	0	4	52	3529	0	0	4406	3420	0	0	0	0	0	0	3861	*15454*
LB1	0	5953	789	0	1948	449	1935	3024	3281	197	0	0	0	1418	6192	4309	*29495*
LB4	0	556	0	2818	2666	2248	929	0	400	292	2237	0	229	0	364	206	*12945*
LA7w	0	0	2440	791	380	0	0	172	16	116	0	3	0	952	787	209	*5866*
LB2	0	0	0	0	0	1127	92	0	0	0	703	0	97	0	0	0	*2019*
LA8	0	0	0	0	0	0	228	0	0	0	151	0	0	205	0	601	*1185*
LB5	0	0	0	0	0	0	1832	2453	0	0	0	0	0	1471	0	1102	*6858*
LA2	0	0	0	0	0	0	0	183	0	201	0	2924	117	0	0	0	*3425*
LA1misc	0	0	0	0	0	0	0	0	0	10	0	426	278	0	0	0	*714*
Sum	*17263*	*16400*	*35771*	*33436*	*43288*	*28706*	*31585*	*30868*	*44757*	*28005*	*11260*	*49600*	*17857*	*35408*	*26672*	*43361*	*494237*
% of operating time	13	8	12	14	18	22	15	13	17	15	8	18	15	14	12	16	*14*

Note: Colors show relative values (red: lowest, green: highest) for time spent in each zone.

Figure 3. Wireless charging statistics.

Tour Generation

The trip energy consumption and other trip-level data were used to identify tours. The starting and ending GPS coordinates of trips were used to identify if those locations were at or out of the base. Noise in GPS data was addressed by considering any trip-end coordinate within 1 mile of the base as being in the base. Further details on the tour generation algorithm can be found in Tanvir et al. (*4*). The recorded data yielded 193 tours for the 20 trucks, and tour-level energy consumptions were calculated for each tour by summing up the energy consumption of the comprising trips:

$$E_{tour}^{Battery} = \sum_{i=1}^{n} E_{trip_i}^{Battery}\ ; n = \text{number of trips in tour} \tag{7}$$

Base Charging Model

Time at the base can be used to charge BETs with conventional charging stations. Battery energy after base charging is as follows:

$$E^{ChargedBattery} = E_{t-1}^{Battery} + \sum_{t=1}^{\alpha T} \eta_C P_t^C(SOC) \tag{8}$$

where $E_{t-1}^{Battery}$ is battery energy before base charging starts, T is time available for base charging (in seconds), α is effective time factor, η_C is charging efficiency, and P_t^C is charging power as a function of battery SOC (energy content of the battery as a fraction of battery capacity). The SOC-P_t^C curve is shown in Figure 4 (*27*). α is introduced to capture the fact that the time spent at base cannot be fully utilized for charging. A portion of the time is spent setting up the trucks at the charger, the truck being engaged in other tasks, or operators simply forgetting to plug in immediately. Table 3 shows parameters values for this study.

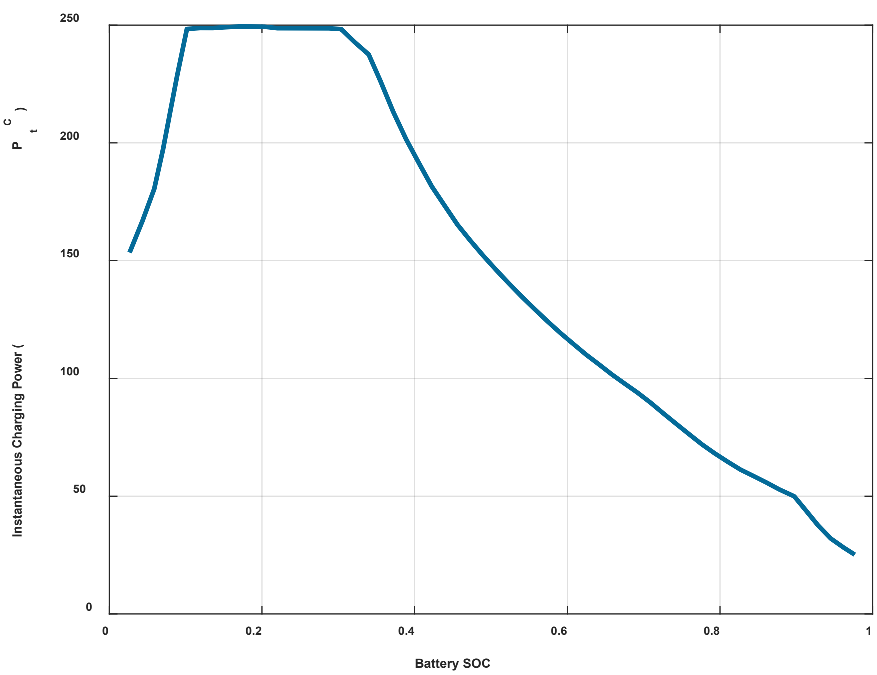


Figure 4. Change of instantaneous charging power with battery SOC.

Table 3. Parameter Values (*1*, *4*, *7*, *28*)

	Parameter	Symbol	Value
Vehicle	Battery size (kWh)	—	377, 565
	Mass (kg)	m	35906
	Coefficient of drag	C_d	0.65
	Front area (m²)	A	8.5
	Coefficient of rolling resistance	C_{rr}	0.008
	Accessory load for EV (kW)	P_{Acc}	2.8
	Wheel efficiency	η_W	0.99
	Final drive efficiency	η_{Fd}	0.98
	Motor efficiency	η_M	0.88
	Battery efficiency	η_B	0.88
Atmosphere	Air density (kg/m³)	ρ	1.161
	Gravity (m/s²)	g	9.8
Wireless charging	Charging power (kW)	P_{WC}	125, 250, 380, 500
	Wireless charging efficiency	η_{WC}	0.9
Base charging	Rated charging power (kW)	—	250
	Charging efficiency	η_C	0.85
	Effective time factor	α	0.8

Note: — in the Symbol column means no symbol is defined for that parameter.

Operational Feasibility Analysis

The modeled system was used to simulate several different scenarios to determine the operational feasibility of BETs. The scenarios (S) are first described for a case in which wireless charging is not available ($P_{WC} = 0$), thus demonstrating the capabilities of the two simulated battery sizes in meeting the activity demands of the trucks without any external aid.

S-1: All Tours Start with 100 Percent SOC

The first step in identifying feasible tours for BETs is to identify the tours within the battery range. EV ranges advertised in specifications are usually mentioned in terms of distance (e.g., miles) and estimated from the energy consumption observed from standard driving cycles (*29*). Real-world energy consumption differs to some extent, so it is worthwhile using the developed model to calculate energy consumption of each tour and see how many of them fall within the range of the modeled truck. S-1 utilizes Eqs. (1)–(7). This scenario assumes that the trucks start with a full battery at the beginning of each tour, and based on this assumption, it was found that 4.1 percent and 0.5 percent of the recorded tours were beyond the range of the modeled BET, with 377 kWh and 565 kWh battery packs, respectively. However, having a full battery at the start of each tour is highly unlikely because the time spent on base in between tours is often shorter than what is needed for a full charge. Conversely, the tours beyond the range of a fully charged battery will stay infeasible regardless of the charging time. Therefore, further analysis of the tours determined to be feasible in S-1 was needed to see what proportion of them stays feasible when charging constraints are considered. To do that, for each battery size considered, the tours beyond range were discarded, assuming those were assigned to diesel trucks, and the tours within range were assigned to BETs. Thus, in the upcoming scenarios, the BETs are carrying out tours in a slightly different order than what was recorded from diesel trucks. A few were skipped.

S-2: Base Charging on Rest Day

The collected data showed that the studied fleet operated six days a week; Sunday was a rest day. Because the drayage tours are scheduled beforehand, the operator kept the rest day for charging the trucks. Thus, this scenario takes the feasible tours for the BETs and simulates them with fully charged BETs that will serve as many tours as possible until their batteries run out. Then, they are recharged on Sunday with a 250 kW charger and again go through the scheduled tours with $E^{ChargedBattery}$ (from Eq. [8]) until the batteries are depleted. Here, Eqs. (1)–(8) were used, and (8) was applied for Sundays only, with $T = 24 \times 3600$ (whole Sunday). This scenario revealed that among the feasible tours identified in S-1, only 71 percent and 81 percent would be feasible, with 377 kWh and 565 kWh battery capacities, respectively.

S-3: Opportunity Charging at Base

S-2 showed that it is essential for BETs to be charged more frequently to reduce the number of infeasible tours. Therefore, opportunity charging at base was considered in this scenario. It is assumed that the time spent at base between two consecutive tours will be used to charge the trucks. Thus, this scenario automatically includes charging on the rest day. Eqs. (1)–(7) gave the tour energy consumption, and Eq. (8) gave the battery energy after opportunity charging at the end of each tour, where T was the time difference between consecutive tours. The next tour started with $E^{ChargedBattery}$ from Eq. (8). This scenario showed that 80 percent and 86 percent of the tours within ranges of 377 kWh and 565 kWh battery packs are feasible when opportunity charging at the base is considered. One solution to serving more tours is increasing the charging power beyond 250 kW, but that is not possible for the simulated trucks because they are rated for 250 kW (*1*).

Adding Wireless Opportunity Charging at Port Terminals

Another way to improve tour completion is to introduce wireless charging at the port terminals. Table 4 shows the fleet-level percentages of feasible tours for the three previous scenarios when considering different wireless charging powers. It should be noted that the values for S-2 and S-3 listed in the table are in terms of all the 193 tours carried out by the diesel fleet, and not the percentage of only tours within range, which are reported in S-2 and S-3 above (those values are from the in-range subset of the 193 tours). The values for S-2 and S-3 are also color-coded in a green-yellow-red scale, green being the most feasible and red being the least, to better illustrate the changes in these values with different wireless charging power and battery capacity.

Table 4. Feasible Tours under Different Scenarios

Battery Size (kWh)	Wireless Charging (kW)	S-1	S-2	S-3
377	No wireless charging	95.9%	70.1%	79.1%
	125	97.9%	71.9%	82.2%
	250	98.5%	71.7%	84.0%
	380	98.5%	71.7%	84.0%
	500	98.5%	72.2%	84.0%
565	No wireless charging	99.5%	80.6%	86.4%
	125	99.5%	82.7%	89.5%
	250	99.5%	83.2%	90.6%
	380	99.5%	83.2%	90.6%
	500	99.5%	83.2%	91.1%

The results for S-1 show tours with energy consumption beyond vehicle range. For the 377 kWh battery pack, wireless charging increased the range, as seen from the increase in the fraction of feasible tours—from 95.9 percent without wireless charging, to 97.9 percent with 125 kW wireless charging, and then to 98.5 percent with 250 kW wireless charging, which then remained unchanged for 380 kW and 500 kW. The 565 kWh battery's range, unsurprisingly, is longer. However, wireless charging even at the highest power of 500 kW did not aid the larger battery pack to cover all the tours—one of the tours has a distance of 303 miles. The infeasible tour's energy requirement surpassed the capacity of the larger battery and was not fulfilled by the additional energy gain at the wireless charging zone(s).

For S-2 with the 377 kWh battery, the fraction of feasible tours increased with the introduction of 125 kW wireless charging, but rather interestingly, slightly decreased for the 250 kW wireless charging and stayed the same for 380 kW before increasing for the higher 500 kW wireless charging. This action was due to the way S-2 was formulated: it discarded the tours identified to be beyond the range in S-1 and used the rest in S-2, which makes the tour sequence in S-2 (and S-3) different from the one recorded in the activity data. In this case, wireless charging of 250 kW and 380 kW made a certain tour fall within the range in S-1, which was deemed beyond range when 125 kW charging was simulated. However, the 377 kWh battery ran out before completing this tour in S-2 in 250 kW and 380 kW charging configurations, whereas the 125 kW case did not need to simulate this particular tour since it was discarded in S-1. Thus, the 125 kW configuration completed an additional tour that could be served with a 377 kWh capacity by means of removing a preceding, more energy-consuming tour from the original tour sequence, and doing so allowed it to appear slightly more feasible. This incident provides a very useful insight in BET operation: tours should be sequenced considering their energy consumption in a way that allows the maximum amount of tour completion with finite battery capacity. Extensive tour reshuffling in this manner was not implemented in this study, other than the construction of S-2 and S-3, but this action is a powerful tool to improve the efficiency of BET fleets. S-2 for the 565 kWh battery shows the fraction of feasible tours increasing up until 250 kW, and then becoming constant, indicating that the energy gains from wireless charging are insufficient to fulfill any additional tour.

The results for S-3 showed improvements over those for S-2, as expected. The fraction of feasible tour plateaued at 250 kW wireless charging for the 377 kWh battery pack, indicating no gains with increased wireless charging powers. However, for the 565 kWh pack, 500 kW wireless charging did increase the fraction of feasible tours even further. Although this analysis shows that the 565 kWh battery pack could serve the largest number of tours, if opportunity charging at base and 500 kW wireless charging at the port terminals were utilized, it still could not serve all the tours. It should also be noted that 250 kW is the highest charging power the modeled truck is rated for and thus cannot benefit from higher charging powers. Nevertheless, all the scenarios analyzed in this study demonstrated the enhanced capabilities of the newer BETs with increased battery capacity, and all the feasibility percentages were high than the values reported in Tanvir et al. (*4*), which simulated an earlier model BET. An even larger battery pack, a higher power charging at the base, and a re-ordering of the tour sequence are some ways to further improve the feasibility of operating a 100 percent BET fleet in drayage application.

Conclusions and Future Work

Drayage has been deemed suitable for electrification since drayage trucks typically work out of a base, return to the base at least once per day, have limited daily mileage, and spend a large portion of driving time in transient modes or creeping. However, there is variation in operating characteristics among different drayage operators. By using real-world activity data of 20 trucks from one drayage operator near the POLA, this study revealed that BETs in the current market would be able to fulfill up to 86 percent of the tours performed by these trucks.

This study also evaluated the effectiveness of utilizing wireless charging zones at port terminals to increase the operational feasibility of drayage BETs. The results show that if wireless charging opportunities at port terminals are available, then BETs will be able to fulfill up to 90 percent of the tours performed by the existing diesel trucks. Installing wireless chargers is a costly task, but doing so at selected zones in port terminals can directly provide en-route opportunity charging to drayage trucks without impacting their operations (e.g., no need for extra trips to and from a charging station).

In terms of future work, an optimal strategy for selecting and prioritizing wireless charging zones should be developed since it may not be financially possible to install all of them at once. As shown in Figure 3, some zones were visited for longer durations than others, which would provide more time for BETs to receive wireless charging. The feasibility analysis will be expanded to examine scenarios with different subsets of wireless charging zones—possibly with different levels of charging power—to identify an optimal solution (the least number of zones yielding maximum number of feasible tours). In addition, on the fleet operational side, the modification of the tour sequence and the use of higher power base chargers to help increase the number of feasible tours will also be investigated.

Case Study II: Inductive Charging at Loading/Unloading Stops

Methodology

Activity data of 2,200 drayage trucks from July to October 2021 were obtained. These drayage trucks usually operate at the terminal regions of Los Angeles, Oakland, Chicago, Houston, Charleston, and Atlanta, just to name a few. For each truck, the ID, latitude, longitude, and GPS date/time were available. In addition, data for each truck at different terminal regions were available, including terminal name, tract name, entry date to the terminal, and exit date from the terminal. The data were not labeled in terms of stops, which means that it was unknown where the home base and stops (at ports, warehouses, etc.) were for each truck. Additionally, the activity data obtained do not follow a particular frequency. The GPS recorded the position of the trucks and the time when a location was passed as the trucks moved along the road. Therefore, if there was no movement, no data were recorded.

In this study, activity data at the terminal regions of the POLB and POLA over two days (August 2–3, 2021) were analyzed for two selected trucks (Truck A and Truck B) as an initial step to assess the necessity of providing en-route opportunity charging. As shown in Figure 5, the data provided were preprocessed and filtered by terminal region and truck ID. Additionally, the GPS date/time differential was calculated to get the time gap between each timestamp. Thus, a cluster of data points on the map with a large amount of time elapsed between timestamps meant a potential home base or warehouse where the truck stopped to rest or to load or unload cargo. To isolate the stops and home-base clusters where the truck spent more time, an unsupervised k-means machine learning model was implemented in Python. The k-means algorithm clusters data by separating them in groups while minimizing the inertia (*30*). This algorithm has been widely used across a range of applications mostly because of its scalability, including for freight GPS data analyses (*31*). In addition, a hyperparameter optimization was performed to determine the optimum number of clusters, random state (for results repeatability), and the maximum number of iterations of the model.

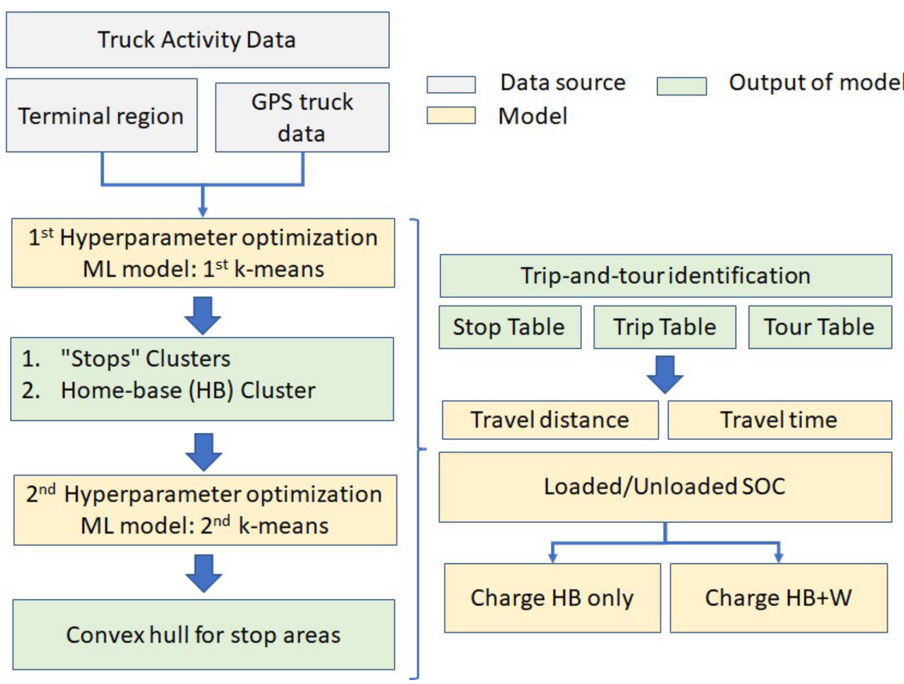


Figure 5. Proposed methodology.

After identifying potential truck stops and the home base, a second k-means model was implemented. The main goal was to obtain the convex hulls for each cluster to identify possible stops of the truck. Thus, based on the original activity of the truck, every time the truck entered the convex hull area and spent a significant amount of time there, the potential stop was labeled as a significant stop and added to the trip-and-tour of the truck. A *truck tour* is defined as the combination of a sequence of trips. A trip usually had one purpose only, such as pick up a container from the port, deliver the container to the warehouse, etc. For this study, a truck tour started and ended at the home-base location. Travel distance and travel time were calculated for trip-and-tour tables using an API for maps, routing, and navigation in Python.

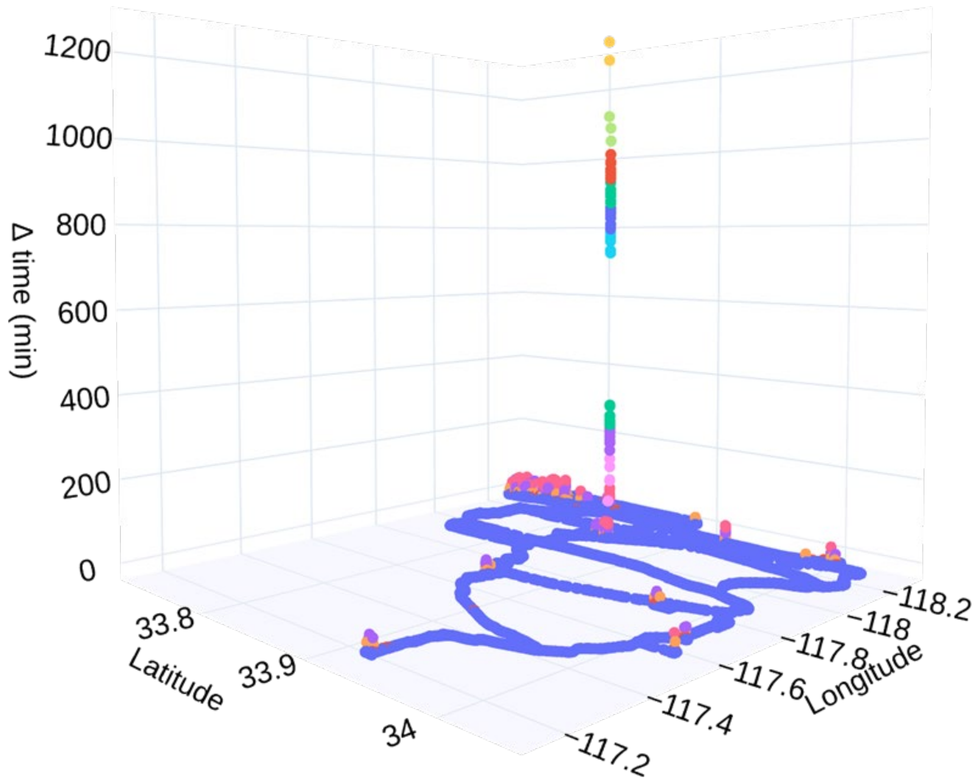
To calculate the SOC, the researchers made the following assumptions in their model:

1. Energy performance efficiency for drayage trucks was adapted from Miyasato et al. (*32*). A 60 percent local and 40 percent freeway operation was assumed, resulting in 3.72 kWh/mi for loaded and 1.48 kWh/mi for unloaded trucks.
2. Trucks are unloaded when coming from the home base and loaded when coming from the port. The other statuses were manually assigned.
3. Battery capacity was adapted from Volvo Truck (*33*), with a usable battery capacity of 300 kWh, assuming an 80 percent battery state of health protection.
4. There was 100 percent SOC at the beginning of the first trip.
5. A 50 kW and 150 kW charger were used, neglecting charging losses.

Finally, two different scenarios were considered: potential en-route opportunity charging at the home base only, and potential en-route opportunity charging at the home base and warehouse stops.

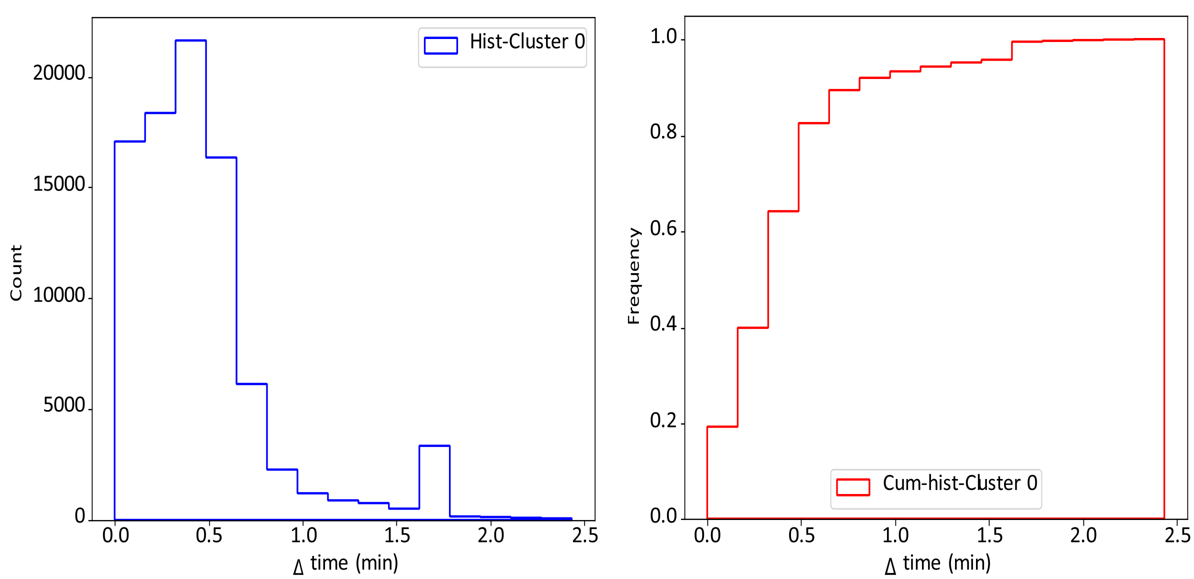
Results and Discussion

Figure 6 shows the results of the first k-means clustering using latitude, longitude, and Δ time in minutes. It is clearly seen that Cluster 0 contains most of the points that represent the truck constantly moving. The aligned vertical clusters with a large Δ time were assumed to be the home base. Hyperparameter optimization was performed, giving the optimum number of clusters of 11 for Truck B and 14 for Truck A. The distributions of Cluster 0 (shown in blue in Figure 6) are presented in Figure 7. As described in the previous subsection (Methodology), Cluster 0 was removed to isolate the clusters where the truck spent more time stopped. Although the 99th percentile of Cluster 0 has a Δ time of 1.65 minutes, there are still some data points with a larger Δ time. Consequently, some corrections were applied to correct the shape of the convex hulls (Figure 8) that had some relevant points being removed during this step. Convex hulls computed as a result of the second k-means performed using only GPS latitude and longitude for Truck A are presented in Figure 8. There were some single-point stops usually located near freeways, so a 0.18 miles radius polygon was constructed around each single-point stop. After getting the convex hulls for the stops for both trucks, the trip-and-tour identification was performed over a smaller dataset from August 2–3, 2021, for both Trucks A and B.



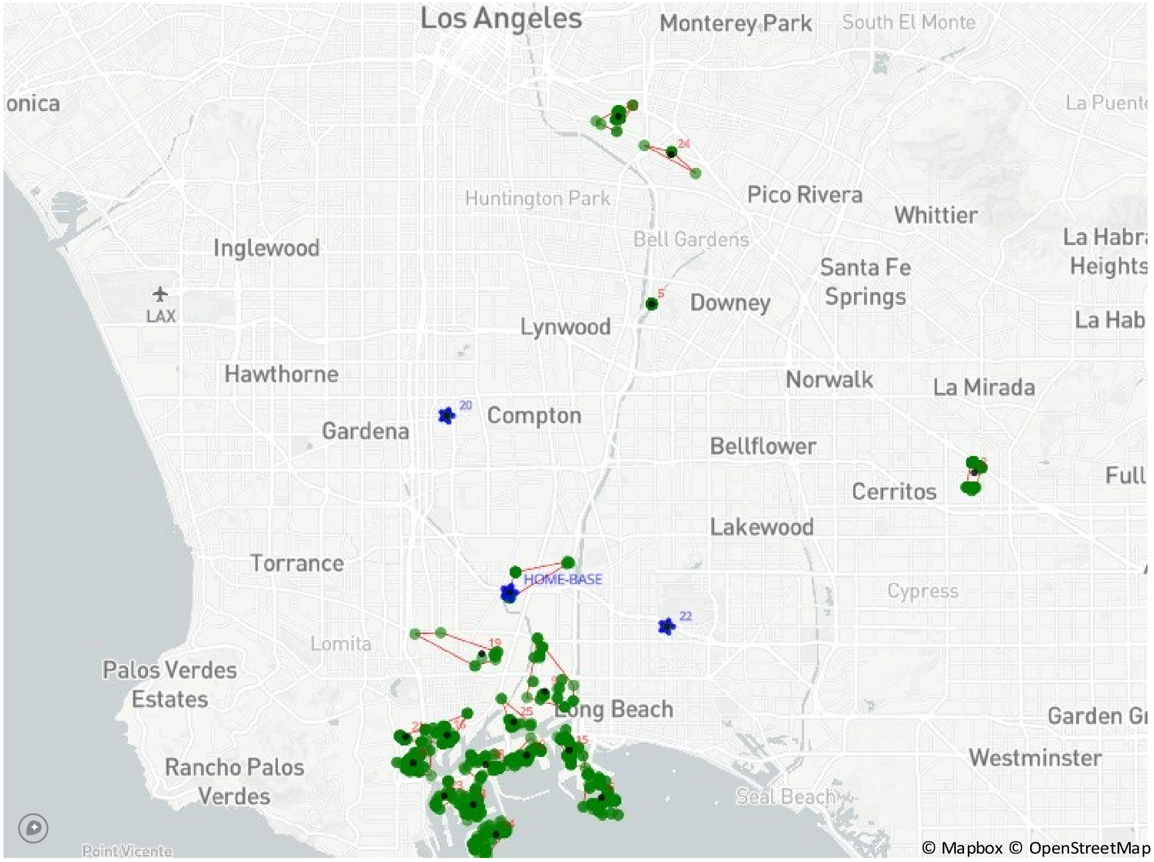
Note: The optimum number of clusters was 14 and 11 for Trucks A and B, respectively.

Figure 6. Results of the first hyperparameter optimization and k-means clustering for Truck A from July to October 2021.



Note: 99th percentile of Cluster 0 has a Δ time of 1.65 minutes.

Figure 7. Histogram (left) and cumulative histogram (right) of Cluster 0 after performing the first k-means for Truck A from July to October 2021.



Note: Convex hulls are shown in red; clusters are shown in green;
home base and single-point stops are shown in blue.

Figure 8. Convex hulls computed for the 26 clusters from the second k-means model for Truck A from July to October 2021.

Figure 9 compares the locations that Truck A and B visited during August 2–3, 2021. It is observed that Truck A visited the port and made four stops, and stopped at the home base for a longer period of time. Conversely, Truck B visited the port and made three stops, and its stops at the home base were shorter. The trip table for Truck B from August 2–3, 2021, is presented in Table 5. This truck had 11 trips, represented by each row in the table, and three tours (from home base to home base) over a two-day period. Cumulative travel distance was 216 miles, and cumulative travel time was 5.2 hours for Truck B. On the other hand, cumulative travel distance was 118 miles and cumulative travel time was 3.6 hours for Truck A.

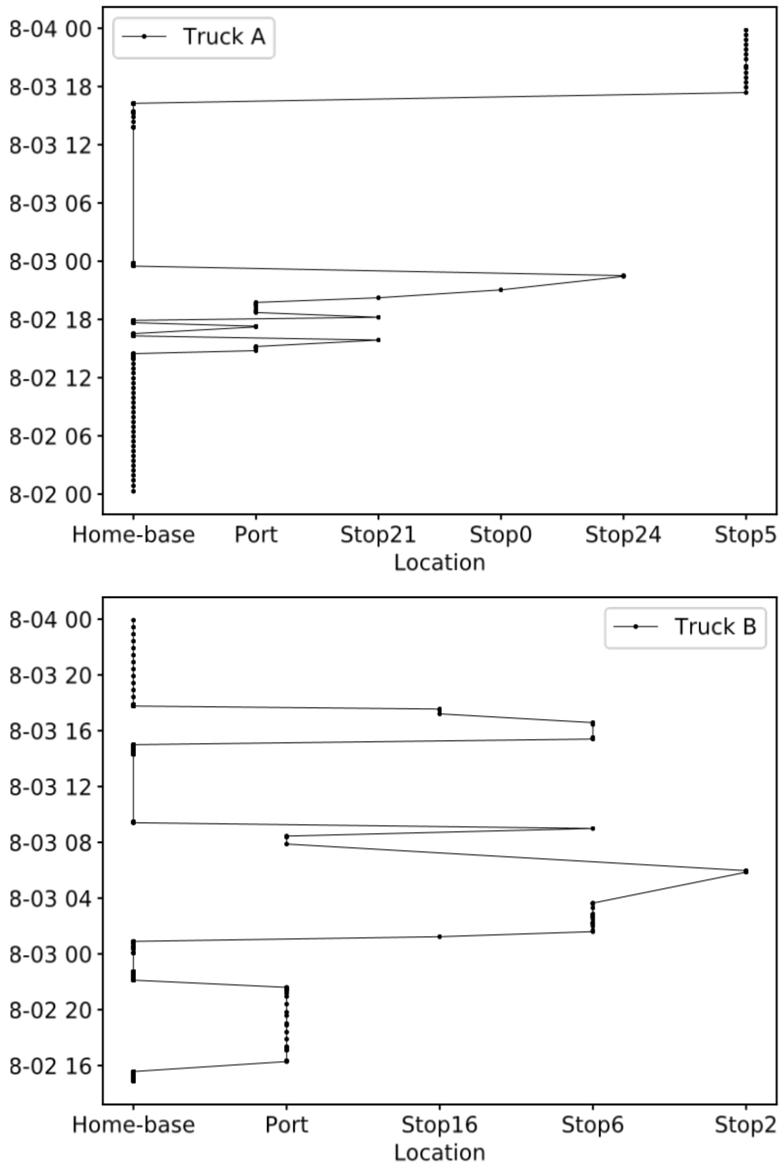


Figure 9. Locations visited by Trucks A (top) and B (bottom) from August 2–3, 2021.

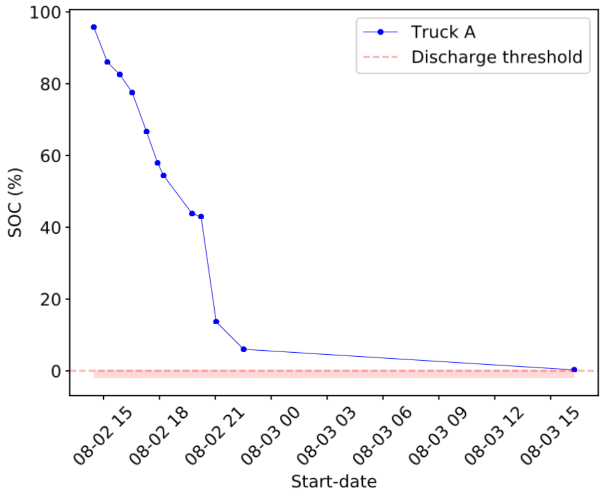
Table 5. Trip Table for Truck B from August 2–3, 2021

Start Location	End Location	Travel Distance (mi)	Travel Time (min)
Home base	Port	6.854	13.403
Port	Home base	6.830	13.238
Home base	Stop 16	4.572	8.535
Stop 16	Stop 6	5.441	12.032
Stop 6	Stop 2	82.318	97.838
Stop 2	Port	76.494	102.145
Port	Stop 6	8.232	18.312
Stop 6	Home base	6.946	13.747
Home base	Stop 6	8.577	14.527
Stop 6	Stop 16	5.507	11.697
Stop 16	Home base	4.212	7.908

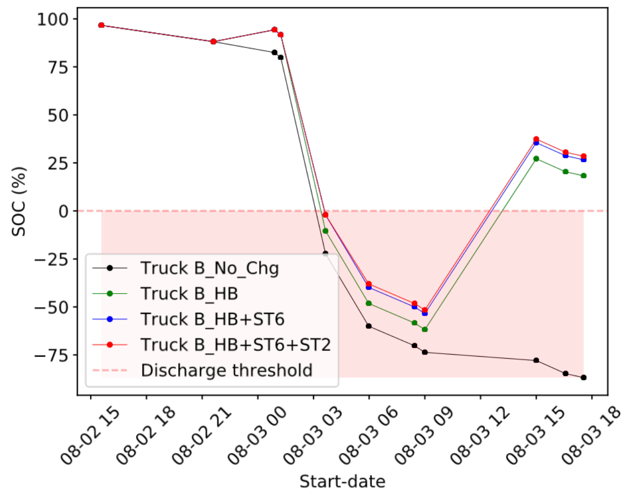
Figure 10 shows different modeled SOC scenarios for Trucks A and B. It is observed that Truck A is able to complete all the trips without requiring en-route opportunity charging (Figure 10a). However, Truck B presents a different case. When modeling the scenario of home base only, en-route opportunity charging with a 50 kW power level (Figure 10b), an improvement in the SOC is observed when compared to the no charging scenario. However, its battery will be discharged before completing the fifth trip from Stop 6 to Stop 2. When modifying the en-route charging scenario at home base + Stop 6, about 100 kWh were added to the battery SOC while the truck spent about 2 hours at this stop (Stop 6). Thus, the truck will be able to complete the fifth trip (Stop 6 to Stop 2) ending with a −2 percent SOC by using its reserve battery capacity, but its battery will be discharged before completing the next trip from Stop 2 to the Port. Moreover, the truck did not spend enough time at Stop 2, so even if some en-route opportunity charging is added at this stop (home base + Stop 6 + Stop 2 scenario), there is no significant improvement in SOC when using a 50 kW charger unless the truck spends more time at this stop. Similarly, SOC scenarios were modeled for Truck B using en-route opportunity charging at a higher power level of 150 kW. For the case of charging at the home base only (Figure 10c), there is no significant difference in the SOC when using a power level of 50 or 150 kW because the truck spent enough time there to be able to fully recharge its battery. Moreover, there is no significant improvement when increasing the power level at Stop 6 from 50 to 150 kW. The truck did not consume a notable amount of energy from previous trips, and it is almost fully charged before starting the fifth trip. Thus, the truck ends with a −2 percent SOC after the Stop 6 to Stop 2 trip, regardless of the power level in Stop 6 because of the travel distance of the trip. In addition, a small SOC improvement is observed when modeling the en-route opportunity charging scenario using a power level of 150 kW at Stop 2. Finally, as shown in Figure 10d, Truck B will be able to complete all of its trips by using a 150 kW power level at Stop 2 and by extending its stay at Stop 2 from 0.11 to 1.07 hours, thereby recharging 161 kWh to its battery.

Conclusions and Future Work

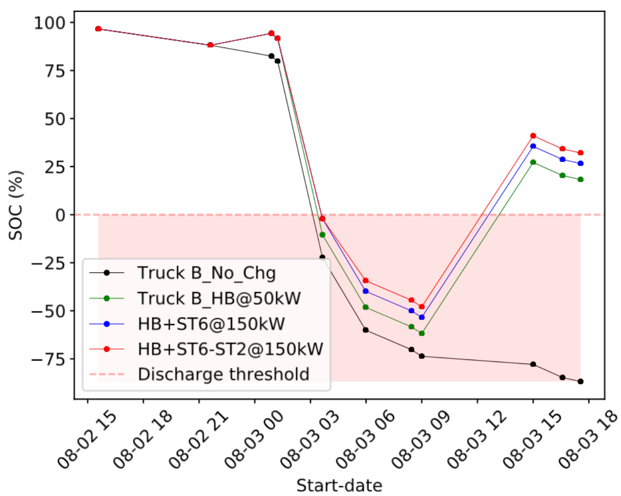
Several targets have been set as California moves forward to achieve carbon neutrality by 2045. Because the target is for all drayage trucks operating in the state to be zero emission by 2035, it is crucial to continue with the modeling efforts to project the quantities, locations, and load of chargers needed to meet statewide electrification goals. Thus, in our attempt to fill the gaps found in the literature of en-route opportunity charging applied to BETs in drayage operations, we propose a data-driven methodology to identify trip-and-tour activity patterns and simulate en-route opportunity charging scenarios at different locations (not only home base) to determine SOC using different power levels. Results show that one of the BETs will only need opportunity charging at the home base in order to complete all of its trips over a simulated two-day period. On the other hand, the other BET will need not only opportunity charging at the home base, but also en-route opportunity charging at loading/unloading stops and an extended length of stop time in one of its stops, which will consequently impact the schedule of the trips that follow. In addition, our results show that there was no significant improvement in the SOC when increasing the charging power level from 50 to 150 kW at the home base and at one of the stops for this truck. These results highlight the importance of providing BETs, even those in short-haul operations, with access to en-route charging opportunities in order to increase the deployment of BETs. Future work will expand the current scope by utilizing data of all trucks in the dataset. We will also identify trip-and-tour patterns using a global set of stops for the entire truck fleet. In addition, we will explore other charging solutions to charge at the port by studying queuing activity patterns of the trucks. Finally, strategic location of charging stations will also be assessed to determine the stops that need to be converted to electric vehicle charging stations to fully optimize battery electric drayage truck operations.



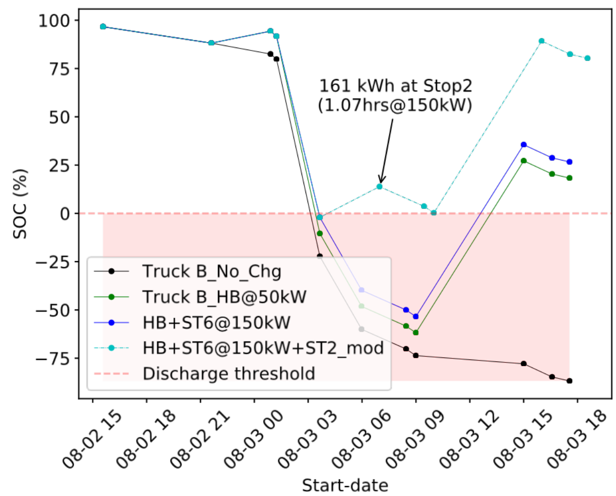
(a) Truck A.



(b) Truck B-50 kW



(c) Truck B-50 kW HB and 150 kW at Stop6 and Stop2



(d) Truck B-50 kW HB, 150 kW at Stop6, modified Stop2

Note: Shaded red area represents the discharge threshold (HB = home base, No Chg = no charging, ST6 = Stop 6, ST2 = Stop 2, ST2 mod = Stop 2 modified).

Figure 10. (a) SOC scenario for Truck A from August 2–3, 2021; (b) SOC scenarios for Truck B from August 2–3, 2021, using a 50 kW charger; (c) SOC scenarios for Truck B from August 2–3, 2021, using a 50 kW charger at home base and 150 kW charger at Stop 6 and Stop 2; and (d) SOC scenarios for Truck B from August 2–3, 2021, using a 50kW charger at home base, 150 kW charger at Stop 6, and 150 kW at Stop 2 but extending its stay from 0.11 to 1.07 hours, adding 161 kWh.

Outputs, Outcomes, and Impacts

This project demonstrated that under considerably realistic operational scenarios, a fleet of current BETs can carry out 86 percent of the tours served by a diesel drayage fleet. Wireless charging zones at strategic port locations aids in increasing that amount further, up to 90 percent. Despite the cost associated with creating such charging zones, it offers the benefit of hassle-free, convenient opportunity charging for drayage BETs without requiring any additional time loss or distance traveled. It also became clear during the analysis that BET fleets can benefit from intelligent tour scheduling aimed at maximizing tour completion and considering BET energy consumption. Effects of two different charging power levels for inductive charging at loading/unloading stops also demonstrated the usefulness of such approaches for range extension and the need for bespoke tour scheduling for BET fleets to fully utilize the benefits of opportunity charging. Implementation of inductive charging for the two cases studied (at ports, and at loading/unloading stops) can offer useful contrasts. For example, wireless charging tracks may be more useful for port locations, whereas charging pads might be suitable for loading/unloading stops. These choices offer flexibility when considering inductive charging facilities for BETs.

Research Outputs, Outcomes, and Impacts

This research has resulted in the following publications.

- Un-Noor, F., Vu. A., Tanvir, S., Gao, Z., Barth, M., and Boriboonsomsin, K. (2022). "Range extension of battery electric trucks in drayage operations with wireless opportunity charging at port terminals." Proceedings of 2022 IEEE Vehicle Power and Propulsion Conference, Merced, CA, November 1–4.
- Garrido, J., Hidalgo, E., Barth, M., and Boriboonsomsin, K. (2022). "En-route opportunity charging for heavy-duty battery electric trucks in drayage operations: Case study at Southern California ports." Proceedings of 2022 IEEE Vehicle Power and Propulsion Conference, Merced, CA, November 1–4.

In addition, the results from this research were presented at the 2022 IEEE Vehicle Power and Propulsion (IEEE VPPC 2022) conference, which took place November 1–4, 2022, in Merced, California, USA.

Technology Transfer Outputs, Outcomes, and Impacts

Technology transfer outputs for this project include the following:

- This work presented methodologies to determine potential locations for wireless charging zones based on vehicle activity data.
- Methodologies for analyzing fleet-level performance for BETs using vehicle activity data were developed and demonstrated.
- Different fleet operation scenarios with varied levels of fidelity to the real-world were formulated and analyzed.
- Limits of current BETs in carrying out typical drayage operations as a fleet were determined.
- Comparative performances of different wireless charging power levels were demonstrated in terms of fleet performance, and the optimal choice for the studied fleet was identified.
- A data-driven methodology to identify trip-and-tour activity patterns for potential en-route opportunity charging of BETs was proposed.
- Range extension effects from different power levels of inductive opportunity charging were analyzed on an individual truck level.

Education and Workforce Development Outputs, Outcomes, and Impacts

Two PhD students were involved in this research:

- Mr. Abdullah Fuad Un-Noor worked on Case Study I: Inductive Charging at Port Terminal Gates. He was a fourth-year PhD student in the Department of Electrical and Computer Engineering at the University of California at Riverside.
- Ms. Jacqueline Garrido Escobar worked on Case Study II: Inductive Charging at Loading/Unloading Stops. She was a fourth-year PhD student in the Department of Electrical and Computer Engineering at the University of California at Riverside.

References

1. VNR Electric Series. https://www.volvotrucks.ca/-/media/vtna/files/en-us/5631_volvo_vnr-electric-brochure_compressed-for-web_f-update.pdf?rev=-1&hash=0DD967A6FD553224B982811B11B65B39.

Accessed Apr. 23, 2022.

2. Tesla. Semi. https://www.tesla.com/semi. Accessed Apr. 25, 2022.

3. Drayage Trucks at Seaports & Railyards. https://ww2.arb.ca.gov/our-work/programs/drayage-trucks-seaports-railyards. Accessed Apr. 25, 2022.

4. Tanvir, S., F. Un-Noor, K. Boriboonsomsin, and Z. Gao. Feasibility of Operating a Heavy-Duty Battery Electric Truck Fleet for Drayage Applications. *Transportation Research Record*, Vol. 2675, No. 1, 2021, pp. 258–268.

5. Patnaik, L., P. S. Huynh, D. Vincent, and S. S. Williamson. *Wireless Opportunity Charging as an Enabling Technology for EV Battery Size Reduction and Range Extension: Analysis of an Urban Drive Cycle Scenario*. 2018.

6. Bi, Z., T. Kan, C. C. Mi, Y. Zhang, Z. Zhao, and G. A. Keoleian. A Review of Wireless Power Transfer for Electric Vehicles: Prospects to Enhance Sustainable Mobility. *Applied Energy*, Vol. 179, 2016, pp. 413–425.

7. Accelerating the EV Transition at the Port of Los Angeles. https://waveipt.wpengine.com/ports/.

8. *Potential Emission Reductions for Select Clean Air Action Plan Strategies*. 2017.

9. Niu, S., H. Xu, Z. Sun, Z. Y. Shao, and L. Jian. The State-of-the-Arts of Wireless Electric Vehicle Charging via Magnetic Resonance: Principles, Standards and Core Technologies. *Renewable and Sustainable Energy Reviews*, Vol. 114, 2019, p. 109302.

10. Sun, L., D. Ma, and H. Tang. A Review of Recent Trends in Wireless Power Transfer Technology and Its Applications in Electric Vehicle Wireless Charging. *Renewable and Sustainable Energy Reviews*, Vol. 91, 2018, pp. 490–503.

11. Arora, S., A. T. Abkenar, S. G. Jayasinghe, and K. Tammi. *Heavy-Duty Electric Vehicles: From Concept to Reality*. Butterworth-Heinemann, 2021.

12. Bi, Z., L. Song, R. De Kleine, C. C. Mi, and G. A. Keoleian. Plug-in vs. Wireless Charging: Life Cycle Energy and Greenhouse Gas Emissions for an Electric Bus System. *Applied Energy*, Vol. 146, 2015, pp. 11–19. https://doi.org/https://doi.org/10.1016/j.apenergy.2015.02.031.

13. Thornton, J. Pulling Power from the Road. *Mechanical Engineering*, Vol. 136, No. 04, 2014, pp. 44–49.

14. Ambrose, H., and M. Jaller. *Electrification of Drayage Trucks: On Track for a Sustainable Freight Path*. 2016.

15. Namboothiri, R., and A. L. Erera. Planning Local Container Drayage Operations Given a Port Access Appointment System. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 44, No. 2, 2008, pp. 185–202.

16. Schulte, F., R. G. González, and S. Voß. *Reducing Port-Related Truck Emissions: Coordinated Truck Appointments to Reduce Empty Truck Trips*. 2015.

17. Zero-Emission Catenary Hybrid Truck Market Study. https://www.gladstein.org/gna_whitepapers/ zero-emission-catenary-hybrid-truck-market-study/.

18. One Way to Curb Freight Emissions: Put Trucks on an Electric Catenary System. https://arstechnica.com/cars/2017/11/one-way-to-curb-freight-emissions-put-trucks-on-an-electric-catenary-system/.

19. CALSTART. Key Performance Parameters for Drayage Trucks Operating at the Ports of Los Angeles and Long Beach. https://calstart.org/libraries-i-710_project-key_ performance_parameters_for_drayage_trucks_operating_at_the_ports_of_ los_angeles_and_long_beach-sflb-ashx-2/.

20. UCLA Luskin Center for Innovation. Zero-Emission Drayage Trucks Challenges and Opportunities for the San Pedro Bay Ports. https://innovation.luskin.ucla.edu/wp-content/uploads/2019/10/Zero_Emission_Drayage_Trucks.pdf.

21. Jones, P. T., and O. Onar. *Impact of Wireless Power Transfer in Transportation: Future Transportation Enabler, or Near Term Distraction*. 2014.

22. Borlaug, B., M. Muratori, M. Gilleran, D. Woody, W. Muston, T. Canada, A. Ingram, H. Gresham, and C. McQueen. Heavy-Duty Truck Electrification and the Impacts of Depot Charging on Electricity Distribution Systems. *Nature Energy*, Vol. 6, No. 6, 2021, pp. 673–682.

23. Hwang, I., Y. J. Jang, Y. D. Ko, and M. S. Lee. System Optimization for Dynamic Wireless Charging Electric Vehicles Operating in a Multiple-Route Environment. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 19, No. 6, 2017, pp. 1709–1726.

24. Deflorio, F., and L. Castello. Dynamic Charging-While-Driving Systems for Freight Delivery Services with Electric Vehicles: Traffic and Energy Modelling. *Transportation Research Part C: Emerging Technologies*, Vol. 81, 2017, pp. 342–362.

25. Scora, G., K. Boriboonsomsin, T. D. Durbin, K. Johnson, S. Yoon, J. Collins, and Z. Dai. Variability in Real-World Activity Patterns of Heavy-Duty Vehicles by Vocation. *Transportation Research Record*, Vol. 2673, No. 9, 2019, pp. 51–61.

26. Gao, Z., Z. Lin, and O. Franzese. Energy Consumption and Cost Savings of Truck Electrification for Heavy-Duty Vehicle Applications. *Transportation Research Record*, Vol. 2628, No. 1, 2017, pp. 99–109. https://doi.org/10.3141/2628-11.

27. Tapered Charging. https://teslatap.com/articles/supercharger-superguide/. Accessed Apr. 24, 2022.

28. Soares, L., and H. Wang. A Study on Renewed Perspectives of Electrified Road for Wireless Power Transfer of Electric Vehicles. *Renewable and Sustainable Energy Reviews*, Vol. 158, 2022, p. 112110.

29. How Does the EPA Calculate Electric Car Range? https://cleantechnica.com/2020/08/18/how-does-epa-calculate-electric-car-range/. Accessed Apr. 24, 2022.

30. Scikit Learn. https://scikit-learn.org/stable/modules/clustering.html.

31. Sharman, B. W., and M. J. Roorda. Analysis of Freight Global Positioning System Data: Clustering Approach for Identifying Trip Destinations. *Transportation Research Record*, Vol. 2246, No. 1, 2011, pp. 83–91.

32. Miyasato, M., and P. Barroca. *Zero Emission Drayage Trucks Demonstration (ZECT 1)*. South Coast Air Quality Management District, Diamond Bar, CA (United States), 2020.

33. Volvo Truck. https://www.volvotrucks.us/trucks/vnr-electric/.