






Application of Wireless Charging at Seaports for Range Extension of Drayage Battery Electric Trucks

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Abstract—Even though heavy-duty battery electric trucks (BETs) have become commercially available, their range limitation still hinders widespread adoption. Drayage has been regarded as a suitable application for early BETs due to typically having limited daily mileage. However, drayage operation can vary widely and some form of range extension may still be needed for BETs operating in this application. In this paper, wireless charging at port terminals is proposed for this purpose. Potential wireless charging zones at port terminals are identified, and efficacy of wireless charging to extend BET range in drayage operation is verified by simulating the activity of 20 BETs from a drayage operator serving the ports of Los Angeles and Long Beach, using a microscopic BET energy consumption model. Furthermore, an optimization problem is formulated for optimal wireless charging zone planning from the port authority’s perspective, considering subsets of the identified zones, and charging power options to choose from, for different budget ranges. In this context, zone planning means determining which areas of the port terminals should be selected for installing wireless charging systems, and what level of charging power should be for each selected zone’s system. For each budget range, the optimization problem is solved using genetic algorithm to determine an optimal zone plan that provides the maximum amount of energy through wireless charging per unit cost of installation. The results show that wireless charging can aid improving activity completion of the simulated fleet by 5%, and further optimizing the zone plan can achieve similar performance with lower cost.

Index Terms—Class 8 truck, drayage operations, electric vehicle, fleet, genetic algorithm, optimization, planning, range anxiety, wireless charging.

I. INTRODUCTION

ELECTRIFICATION of heavy-duty trucks is a key strategy for reducing pollution from the transportation sector

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[1]. Electrifying these vehicles, however, is challenging due to technical limitations such as low energy density of batteries [2]. Even though these limitations are slowly being overcome, and commercial battery electric trucks (BET) are becoming available [3], [4], the range of these BETs are still not enough for all freight applications, especially the ones over long distances. The current BETs make more sense when considered for shorter-haul applications, which are within their driving range. Drayage is one such application which renders itself particularly suitable for BETs. It involves the transportation of containers and bulk by heavy-duty trucks in-between ports, intermodal railyards, and near-by warehouses [5]. Trucks engaged in drayage generally work from a base where they usually return at least once a day, drive a limited number of miles daily, and spend a significant amount of driving time creeping or in transient modes. The limited daily mileage of drayage trucks renders them suitable for current BETs, which have limited range. Regularly returning to base creates possibility for overnight and opportunity charging. And the significant amount of creeping and transient modes in driving favors BETs over diesel trucks as the BETs, equipped with regenerative braking system, would consume significantly less energy in those conditions while also causing less air pollution.

Due to the potential of BETs to replace the ever-expanding fleet of polluting diesel drayage trucks, many past studies addressed this topic from different angles. More specifically, the drayage operation at the San Pedro Bay port complex (Port of Los Angeles and Port of Long Beach) generated significant research interest. These past works are particularly useful in highlighting the relevance of this paper, as it too uses drayage fleet operational data at these ports as a case study (the data is described in Section II-A). In 2018, You and Ritchie studied drayage truck operation at these ports using data collected by global positioning system (GPS) units installed on trucks. They noted that most drayage tours were completed within a day, and tours had repetitive patterns (a trait not shared by other commercial trucks) [6]. Giuliano et al.’s 2021 research mentioned the increasing truck traffic and emissions resulting from the rise in freight shipment, as the motivation to study BETs. They noted the range and charging limitations of BETs in the near-term, but also mentioned that with enhanced performance and reduced cost, BETs could be suitable for increasingly more applications. Their comparative study of BETs with hybrid trucks showed that BETs were more effective in reducing air toxins. They also

suggested investment in charging infrastructure to promote BET use [7]. Ramirez-Ibarra and Saphores tackled the cost issue of replacing the diesel drayage trucks with zero emission alternatives at the San Pedro Bay port complex from the perspective of environmental and health costs incurred by diesel pollution. Their analyses showed that compared to 2012, significant amounts of premature deaths and asthma attacks could be reduced by 2035 by switching to zero emission technologies, even though the drayage fleet was expected to expand by 145%. Such steps would aid significantly to reduce health issues in disadvantaged communities [8].

However, BETs are not a perfect match for drayage applications yet as a previous study revealed that a BET fleet is incapable of operating at the same level of a diesel fleet under similar operational conditions [9]. BETs were held back by the downtime they received, which was insufficient to significantly recharge their batteries. Whereas for diesel trucks, that downtime duration was sufficient for refueling. The BETs in [9] were considered to be charged only at the base. It thus underscores the need for providing convenient out-of-base charging opportunities for drayage BETs, and wireless charging is one potential solution to achieve that. Hydrogen fuel cell electric trucks had also been explored as a potential zero-emission replacement for port trucks [10], [11], [12], but this paper focuses solely on overcoming current limitations of BETs for this application.

Wireless charging has gained popularity in recent times as a solution to combating range anxiety [13], [14]. As this technology can charge vehicles in motion, it removes the necessity to stop vehicles in order to charge. Wireless charging essentially extends the effective range of electric vehicles (EV), allowing them to travel longer distances with a certain battery size. It has also been considered more convenient and cost-effective compared to stationary charging systems and battery swapping [15], [16]. Wireless charging has been pitched for electric buses [13], [17], [18], which follow fixed routes, have to operate on a schedule, and have limited downtime that minimizes the chance of conventional charging. With wireless charging systems installed in the operating route, the buses can conveniently replenish their batteries without hampering the schedule. This approach can be applied to drayage trucks, as they too operate on a tight schedule that does not allow for significant downtime, and they are highly likely to visit a certain location: the port. Installing wireless charging systems at ports thus appears as a useful solution to extend range of drayage BETs, which could significantly aid them to go toe to toe with the diesel variants.

For investigating the efficacy of wireless charging for a drayage BET fleet operation, this work begins by developing a microscopic BET energy consumption model. Such approaches are well-documented in literature [19], [20], [21], [22], [23], and here, it is used to simulate the operation of BETs using real-world operational data collected from diesel drayage trucks. Conventional charging at the home base, and wireless charging at port locations is integrated in the simulation model. This combined simulation model provides the energy usage due to BET activity, and gains from regeneration, conventional charging at home base, and wireless charging at specific wireless charging

zones. Effect of wireless charging for range extension can be clearly observed from the simulation results.

Port locations most visited by trucks are good candidates for installing wireless charging systems. However, there can be many such locations in a port, and the port authority is likely to have limited resources at their disposal for converting them into wireless charging zones. Thus, they have to select a few spots which would provide the best charging opportunity. If there are more than one option for wireless charging systems, for example, different power ratings, they would also have to decide which power rating to choose for which zone, considering the associated cost and resulting return in terms of charging energy gains. This form of optimal charging station planning has been studied heavily for stationary charging stations, and different approaches were demonstrated to come up with an optimal plan considering certain constraints and objectives [24]. Previous studies focused on charging station costs [25], [26], [27], power loss [28], [29], profit maximization [30] etc. A plethora of optimization techniques have also been used to achieve the optimal charging station plans from the formulated problems. These include balanced mayfly algorithm [25], cat swarm optimization, teaching–learning based optimization [26], genetic algorithm [27], and multi-population genetic algorithm [31].

The contribution of this paper is in evaluating wireless charging at seaports for range extension of drayage BETs for effective fleet operation. Additionally, it presents methodology to optimally plan wireless charging at ports. The rest of the paper is arranged as follows. Section II describes the data used, simulation models, and analyses framework. The results are presented and discussed in Section III. Finally, the conclusions are drawn in Section IV.

II. METHODS

This paper utilized real-world in-use activity data from a drayage fleet to identify port locations best suited to serve as wireless charging zones. As it is unrealistic to install wireless charging systems at all of them, an optimization problem was then formulated for determining which selection of these zones serve best as wireless charging zones, and what should be the charging power rating at each of the selected zones, considering budget constraints. A BET model, and a fleet operation framework were formulated next. The BET model allowed calculating wireless charging gains from the determined zone plans at a microscopic level. The fleet operational framework was then used to verify a BET fleet's capability in carrying out tasks performed by diesel trucks, aided by range extension from wireless charging.

A. Data

Truck activity data from a fleet of 20 class-8 diesel trucks was used in this paper. This fleet operated from their base located about a mile away from the port of Los Angeles, and primarily served the San Pedro Bay port complex (Port of Los Angeles and Port of Long Beach), the Inland Empire area, and the Greater Los Angeles Metropolitan area. Occasional service destinations

TABLE I
SUMMARY STATISTICS FOR TRIPS IN DATASET

	Average	Range
Trip distance (miles)	3.6	0.6-8.0
Trip duration (minutes)	21.0	5.0 – 42.8
Trip speed (miles/hour)	5.6	1.8 – 8.4
Time spent idle	63.6%	43.7% - 88.9%
Time spent braking	36.2%	10.9% - 56.3%

TABLE II
SUMMARY STATISTICS FOR TOURS IN DATASET

	Average	Range
Tours per day	2.2	1 – 7
Tour distance (miles)	58.9	5.7 – 122.5
Running time (minutes)	244.3	43.6 – 401.9
Time spent at base (minutes)	21.1	0 – 44.9
Time spent at stops outside base (minutes)	262.8	0 – 490.6

included locations in inland Northern California and Central Valley. Data loggers were used to collect over 170 engine control unit (ECU) parameters and GPS data (e.g., speed, timestamp, latitude, longitude) at 1 Hz. The collected truck activity data was segmented in terms of trips, which was later used to identify tours. Trip was defined as travelling between two nodes, while tour represented a chain of trips starting from the base and finally returning to it. The data extracted from the logger was put through multiple processing steps for cleaning and correction, trip identification, and origin and destination cloaking of trips for confidentiality [32]. Road grade data was added for freeway portions of trips using map-matching. Due to unavailability of grade data for non-freeway portions, non-freeway grades were considered 0 (flat terrain). The final dataset yielded truck activity for the week of Monday, Jan 23, 2017 through Friday, Jan 27, 2017. Tables I and II provide summary statistics for trips and tours in the dataset, respectively.

B. Identifying Wireless Charging Zones

In this paper, potential wireless charging zones at the San Pedro Bay port complex were identified by studying recorded truck activity. Port locations where the trucks spent significant amounts of time queuing or stopping (for example, terminal gates) were selected, as this allows the most charging opportunity. To do this, first the port terminals at the complex were identified (Fig. 1). Then, using the activity data, stop/queuing instances within these terminal boundaries were estimated. Locations in the terminals having a cluster of stop/queuing data points were

identified as potential wireless charging zones. The stop/queuing data points were obtained by first filtering the activity data by speed (speed = 0) to find out truck stop/idling instances. These data points were then matched with aerial images to estimate queuing areas. Polygons were drawn around these areas, and that yielded the potential wireless charging zones (red areas in Fig. 1). Roadway lengths covered by the identified zones were measured, wireless charging systems in the zones have to provide charging along these lengths. It was assumed that in these zones, there would be one dedicated lane for BETs with wireless charging systems installed.

The collected GPS data, with the aid of geofencing, was then used to identify instances of truck presence in these zones Fig. 2. There was some noise in the GPS data, which showed vehicle positions changing even when the trucks were stationary (speed = 0). This was corrected by ignoring GPS data showing vehicles moving out of a zone when speed was zero, thus considering the vehicles remained in that zone. Finally, consecutive matched geofence data points were grouped together to create potential charging events, assuming those zones to have wireless chargers installed. A summary of these charging events for 16 trucks is shown in Table III. Four of the 20 trucks did not visit any of the wireless charging zones identified, and thus, did not experience any charging event. The power delivered by wireless charging to truck j in zone i during each second, t was calculated as:

$$P_{t,i,j}^{WChrg} = P_{WC_i} \eta_{WC_i} \quad (1)$$

where P_{WC_i} is rated wireless charging power and η_{WC_i} is wireless charging efficiency in zone i .

C. Optimal Zone Planning

The total amount of energy a wireless charging zone can deliver to trucks depends on the amount of time the trucks stay in it. This energy for each zone, i , can be calculated as:

$$E_i^{WChrg} = \sum_{j=1}^m P_{t,i,j}^{WChrg} T_j \quad (2)$$

where T_j is the total amount of time (in seconds) truck j spent in zone i , and m is the total number of trucks that visited zone i .

The cost for installing wireless charging system at zone i can be calculated as:

$$C_i = L_i U_{P_{WC_i}} \quad (3)$$

where L_i is the length of zone i in miles, and $U_{P_{WC_i}}$ is the unit cost per mile for installing wireless charging system. This unit cost, $U_{P_{WC_i}}$, depends on the rated charging power selected for zone i , P_{WC_i} .

It can be seen from Table III that all 23 zones were not visited by each of the 16 trucks (recall that four of the 20 trucks did not visit any zone at all). Also, some zones saw more truck presence than others. (2) shows that the energy provided by each zone depends directly on the time spent by trucks in each zone. (3) on the other hand, shows that the cost of installing wireless charging systems in each zone depends on the zone length, and the rated charging power of the installed system: which controls

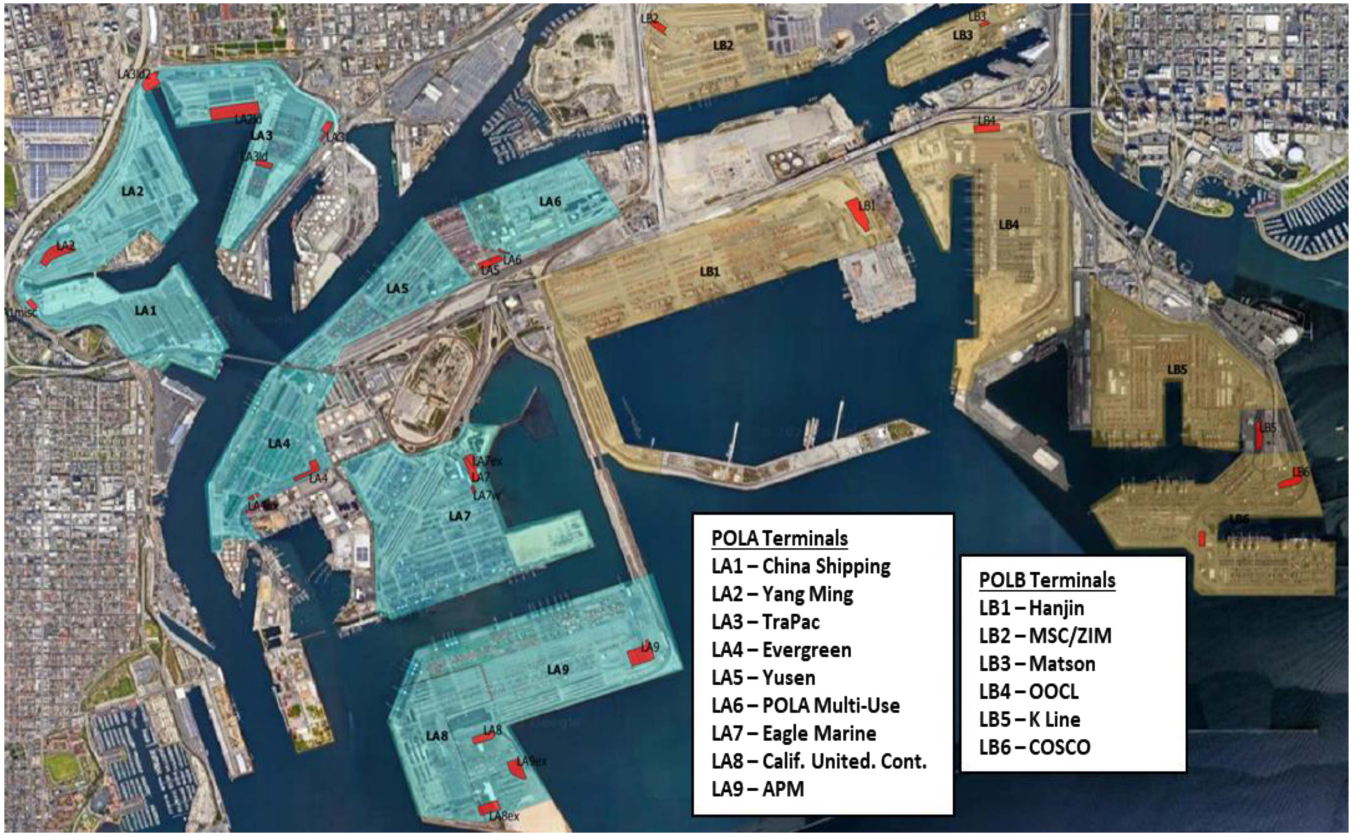


Fig. 1. Locations identified to place wireless chargers (in red) at different terminals (marked by translucent turquoise and brown polygons) at the Port of Los Angeles (POLA) and the Port of Long Beach (POLB).

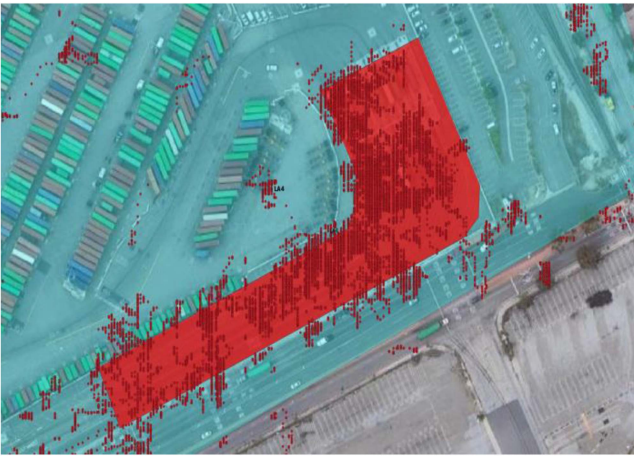


Fig. 2. Identifying truck presence (red dots) in a potential wireless charging zone (red polygon).

the unit cost. For zone planning, we need to select specific zones from the total of 23, and the charging system powers in those zones, in a way that conforms to the budget allocated for this task. For a certain budget cap, this selection can be done in multiple ways. For example, one could choose to install costlier, higher-powered charging systems in a few zones, or could opt

for installing a cheaper, lower-powered system in more zones. There could also be other choices where some zones receive the higher-powered system, and some zones the lower-powered one. The same budget cap could be met with different such selections. Depending on the selected zones, some selections (e.g., more total truck presence with less total roadway length to cover) could deliver more energy to the trucks than others (e.g., less total truck presence with more total roadway length to cover). The option of varying the charging power adds one more dimension to this consideration, as a higher-powered system would provide more energy compared to a lower-powered one during a certain amount of truck presence, but would also cost more, and that might bar including additional zone(s) by depleting the budget sooner. Thus, an optimal zone plan have to select specific zones, and the charging powers for each of them, in a way that the maximum amount of energy delivery can be achieved for a certain budget limit. In other words, this optimal selection would provide the maximum amount of energy delivery per unit amount of expenditure, for a given budget. It can also be called as the most efficient plan. To formulate this optimization problem, the objective function is thus defined as following:

$$\text{Objective Function} = \sum_{i=1}^n E_i^{WChrg} / \sum_{i=1}^n C_i. \quad (4)$$

TABLE III
WIRELESS CHARGING STATISTICS

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	0	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

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

where n is the total number of wireless charging zones. Equating from (1), (2), and (3), the objective function can be expressed as a function of the rated charging power at each zone:

$$f(P_{WC}) = \sum_{i=1}^n \sum_{j=1}^m P_{WC_i} \eta_{WC_i} T_j / \sum_{i=1}^n L_i U_{P_{WC_i}} \quad (5)$$

The optimization problem can then be formulated as:

$$\text{maximize } f(P_{WC}). \quad (6)$$

$$\text{subject to } \sum_{i=1}^n L_i U_{P_{WC_i}} \leq \text{budget} \quad (7)$$

To simplify the optimization problem, we considered three choices of rated charging power for each of the n zones, as 0 kW, 125 kW, and 250 kW. 0 kW essentially means not installing a wireless charging system at a zone; in other words, that particular zone not being selected for wireless charging. Recent wireless charging demonstration projects focused on systems with 125 kW, 250 kW, 380 kW, and 500 kW [33]. However, the BET modeled in this paper allows a rated charging power of up to 250 kW [3]. Therefore, 150 and 250 kW were selected as the options in this paper. Current publicly available information on wireless charging quoted a cost of \$1.9 million for a mile-long charging zone [34], where charging rate could reach 150 kW for vehicles equipped with five receivers, each rated for 30 kW

[35], [36]. For the lack of better data, this \$1.9M/mile cost was considered for the 125 kW charging system, as it is closest to the charging power of the \$1.9M/mile system. The other charging power of 250 kW was assumed to cost 1.5 times higher, \$2.85M, considering some cost saving due to economy of scale. This was purely based on assumption, as no data was available. The cost for 0 kW is \$0, as it means not installing any charging system. For budget constraints, a lower budget would require selecting zones with better yield (energy delivery per unit cost). Higher budgets would allow including zones with gradually less yield. To demonstrate the formulated optimization problem, a budget range was considered, with C_{lb} as the lower bound and C_{ub} as the upper bound. With these considerations, the optimization problem can be expressed as:

$$\text{maximize } f(P_{WC}) \quad (8)$$

$$\text{subject to } C_{lb} \leq \sum_{i=1}^n L_i U_{P_{WC_i}} \leq C_{ub} \quad (9)$$

$$P_{WC_i} \in \{0, 125, 250\}, i = 1, \dots, n \quad (10)$$

This optimization problem was implemented in MATLAB 2022a, using its genetic algorithm solver from the Global Optimization Toolbox [37]. This solver is designed to minimize the objective function, thus the negative of (8) was provided as the objective function ($-f(P_{WC})$); minimizing $-f(P_{WC})$ means

maximizing $f(P_{WC})$. The constraint in (9) was included in the objective function formulation in a way that the zone plans with costs outside the specified budget range were penalized and thus not chosen as optimal solutions.

D. BET Model

To examine the effect of the optimal charging zone plans on a drayage fleet, a BET fleet was considered to carry out the exact same tasks recorded in the collected data. Energy requirement of each truck in the fleet was represented by a microscopic energy consumption model, expressed as following:

$$E_t^{Battery} = E_t^{Tract} + E_t^{Acc} - E_t^{Regen} - E_t^{WChrg} \quad (11)$$

where $E_t^{Battery}$ is battery energy consumption in each second; E_t^{Tract} , E_t^{Acc} , E_t^{Regen} , and E_t^{WChrg} are instantaneous tractive energy consumption, accessory load consumption, energy regeneration from braking, and energy gain from wireless charging, respectively. E_t^{WChrg} was obtained using (2). The rest were derived as:

$$E_t^{Tract} = \frac{P_t T}{\eta_W \eta_{Fd} \eta_M \eta_B}; \forall (P_t \geq 0) \quad (12)$$

$$P_t = m v_t a_t + 0.5 \rho C_d A v_t^3 + C_{rr} g m v_t \cos \theta + g m v_t \sin \theta \quad (13)$$

where m is BET mass, v_t is instantaneous speed, a_t is instantaneous acceleration ($a_t = v_{t+1} - v_t$), 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, θ is angle of inclination of the road; $\eta_W, \eta_{Fd}, \eta_M, \eta_B$ are efficiencies of wheel, final drive, motor, and battery, respectively. P_t gives tractive power consumption in each second, which is used in (12) to get the tractive energy consumption, considering $T = 1$ as the data is 1 Hz. η_B was calibrated for matching the simulated BET's rated range (275 miles with 565 kWh battery [3]) weighing 80000 lbs.

$$E_t^{Acc} = P_{Acc} T \quad (14)$$

where P_{Acc} is the rated accessory load, and $T = 1$.

$$E_t^{Regen} = P_t \eta_W \eta_{Fd} \eta_M \eta_B; \forall (P_t < 0) \cap (v_t > 5) \cap (a_t < 3) \quad (15)$$

Battery energy consumption for each trip was calculated as:

$$E_{trip}^{Battery} = \sum_{t=1}^T E_t^{Battery}; T = \text{trip duration} \quad (16)$$

Average trip battery energy consumption was 25 kWh, with minimum and maximum trip consumptions being 0.009 kWh and 515 kWh, respectively.

E. Fleet Operation Model

Trip-level data was used for tour construction. For each trip, starting and end GPS coordinates were used to determine if the trips started and/or ended at the base. A trip starting at the base was marked as the start of a tour, and the successive trip that ended at the base indicated the end. If a trip started and ended at

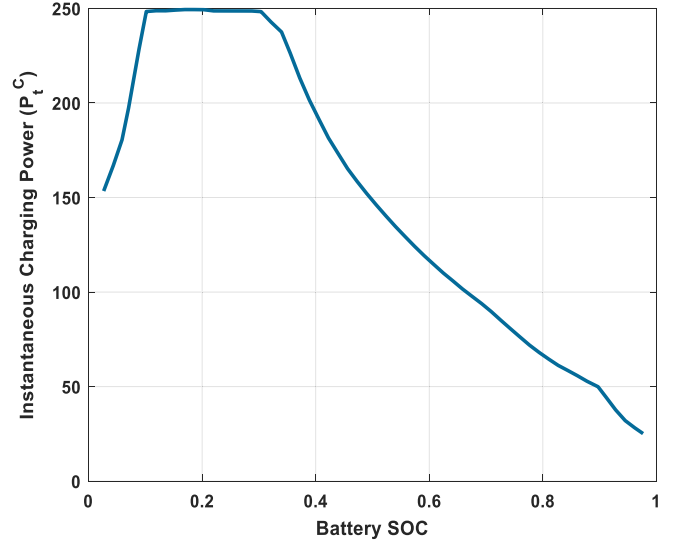


Fig. 3. Battery SOC-dependent charging power assumed for BET charging at base.

the base, it would be a tour by itself [9]. For our dataset with 20 trucks, 193 tours were identified. Battery energy consumption in each tour can now be calculated as:

$$E_{tour}^{Battery} = \sum_{i=1}^k E_{trip_i}^{Battery}; k = \text{number of trips in tour} \quad (17)$$

Using (17), battery energy consumption for each tour, or in other words, how much a fully charged battery pack would be depleted to complete each tour, was calculated. Average tour battery energy consumption was 120 kWh, with minimum and maximum tour consumptions being 0.3 kWh and 708 kWh, respectively.

As tours requiring energy more than the battery capacity could not be completed, a tour schedule was created for the BET fleet excluding such tours (in this case, one tour) from the total of 193. In our fleet operational framework, a fleet of 20 BETs were considered, each replacing a diesel truck to carry out the exact same tours, with the exclusion of tour(s) beyond battery range. Each BET was assumed to start with a fully charged battery at the beginning of the simulation. The batteries got depleted as the BETs travelled for each tour; they received wireless charging if available. When the BETs returned to the base at the end of a tour, they received opportunity charging with conventional charging stations during the time they spent at the base in-between tours. Battery energy after base charging was calculated by:

$$E^{ChargedBattery} = E_{t-1}^{Battery} + \sum_{t=1}^{\alpha T} \eta_C P_t^C \quad (18)$$

where $E_{t-1}^{Battery}$ is battery energy before base charging, α is effective time factor, T is available time for base charging in seconds, η_C is charging efficiency, and P_t^C is charging power – which is a function of battery state of charge (SOC). The SOC- P_t^C plot is shown in Fig. 3 [38]. α represents the portion of

TABLE IV
PARAMETER VALUES [3], [9], [33], [39]

	Parameter	Symbol	Value
Vehicle	Battery size (kWh)	-	565
	Mass (kg)	m	35906
	Coefficient of drag	C_d	0.65
	Front area (m ²)	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/m ³)	ρ	1.161
	Gravity (m/s ²)	g	9.8
Wireless Charging	Rated charging power (kW)	P_{WC}	0, 125, 250
	Wireless charging efficiency	η_{WC}	0.9
	Per mile cost (\$M)	U_{PWC}	0, 1.9, 2.85
Base Charging	Rated charging power (kW)	-	250
	Charging efficiency	η_C	0.85
	Effective time factor	α	0.8

TABLE V
FEASIBLE TOURS UNDER DIFFERENT SCENARIOS

Scenario	No Wireless Charging	125 kW in all zones	250 kW in all zones
% Feasible Tours for BET Drayage Fleet	86%	90%	91%

time at base actually utilized for charging, as trucks are unlikely to be plugged in the second they arrive at base. Table IV shows the parameter values used in this study.

III. RESULTS AND DISCUSSIONS

Effect of wireless charging on the studied drayage fleet tour completion is analyzed first for two straightforward scenarios: installing either 125 kW or 250 kW charging systems in all identified zone. The outcome of this analysis is shown in Table V, which shows that both these approaches improve tour completion compared to the case with no wireless charging; installing 250 kW systems in all zones improve tour completing by 5%, while the 125 kW system achieves 4% improvement. The distribution of individual tour battery depletion for two cases: no wireless charging, and 250 kW wireless charging at all zones,

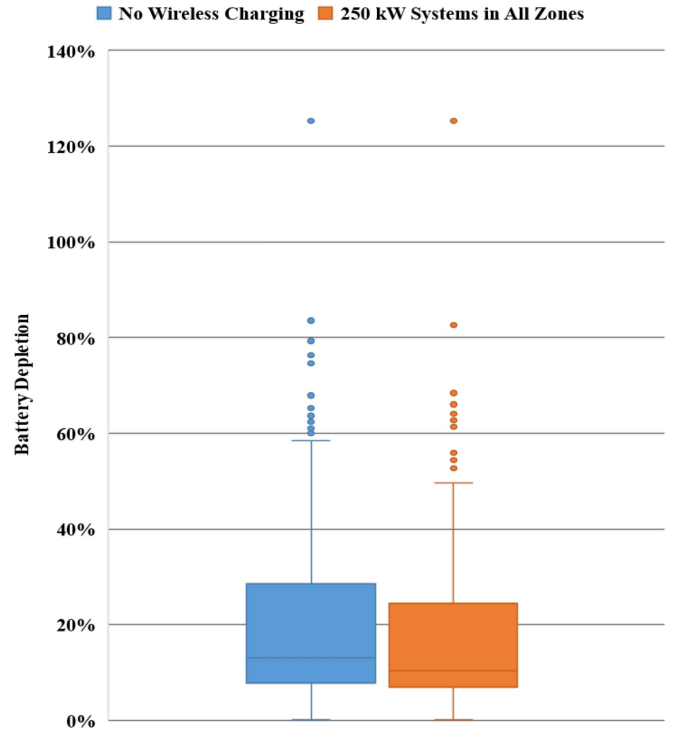


Fig. 4. Distribution of battery depletion, shown as box plots. One specific tour depleted the battery 125% for both cases, indicating that this tour is out of range for the simulated BET, and it did not visit any wireless charging zone.

are shown in Fig. 4. Tours passing through wireless charging zones allowed batteries to be charged, thus the case with wireless charging depleted the battery less. From this figure, it can be seen that one specific tour was depleting 125% of the battery capacity, which means the simulated BET would not be able to cover this tour even if it began with a fully charged battery. This tour is simply out of range. Also, range extension from wireless charging did not alter the amount of battery depletion for this tour. This indicates that this tour did not visit any of the wireless charging zones.

We can now look at the optimized plans and see how a mix of charging systems can be placed at specific zones to achieve better charging performance, rather than blanketing all the zones with a single selection of charging system. Table VI shows the optimal zone plans obtained from conducting the optimization with genetic algorithm. Truck operating times in different zones, and zone lengths are also presented with a color code in this table. The colors show relative values (red: lowest, green: highest). Solving the formulated optimization problem gives optimal zone plans for a specified budget range. This zone plan specifies a wireless charging system from the three options of 0 kW, 125 kW, and 250 kW, for each of the 23 zones. If a zone is paired with a 0 kW system, it means that this zone should not have any charging system installed. This zone plan provides the maximum amount of wireless energy delivery per unit cost of installation. Therefore, if the optimization is not mandated to spend a minimum amount of money, it provides the absolute best plan which maximizes the objective function (8). This can be seen from Table VI, for the case with no lower budget limit.

TABLE VI
OPTIMAL WIRELESS CHARGING ZONE PLANS FOR DIFFERENT BUDGET RANGES

Zone	Operating Time (seconds)	Length (mile)	Charging Power at Zones (kW)						
			Budget: No lower limit	Budget: \$1-2 Million	Budget: \$2-3 Million	Budget: \$3-4 Million	Budget: \$4-5 Million	Budget: \$5-6 Million	Budget: No upper limit
LA7	131116	0.09	250	250	250	250	250	250	250
LA9	81115	0.10	250	250	250	250	250	250	250
LA3ld2	47933	0.08	0	250	250	250	250	250	250
LA4	42613	0.16	0	0	250	250	250	250	250
LB1	29495	0.13	0	0	250	250	250	250	250
LA7ex	26520	0.05	0	250	250	250	250	250	250
LA8ex	16670	0.09	0	0	0	250	250	250	250
LA9ex	16251	0.08	0	0	0	250	250	250	250
LA2ld	15454	0.22	0	0	0	0	0	250	250
LB4	12945	0.11	0	0	0	250	250	250	250
LA5	12629	0.10	0	0	0	0	250	250	250
LA3	10007	0.08	0	0	0	250	250	250	250
LB6	9057	0.15	0	0	0	0	250	0	250
LA3ld	7648	0.07	0	0	125	0	250	250	250
LB5	6858	0.10	0	0	0	0	0	125	250
LA7w	5866	0.02	0	125	250	250	250	250	250
LA4ex	5387	0.03	0	0	0	250	250	0	250
LA4ex2	4837	0.02	0	125	125	250	250	250	250
LB6misc	4493	0.05	0	0	0	0	0	250	250
LA2	3425	0.16	0	0	0	0	0	250	250
LB2	2019	0.06	0	0	0	0	0	250	250
LA8	1185	0.10	0	0	0	0	0	0	250
LA1misc	714	0.04	0	0	0	0	125	0	250

This plan called for installing the 250 kW charging system at the two zones having the most truck presence, and relatively smaller lengths (can be seen from the colors). More truck presence means more energy delivery, while smaller length translates to lower costs. Also, as the higher charging power of 250 kW provides double the energy compared to 125 kW, but costs less than double (1.5 times), choosing 250 kW gives the maximum energy delivery per unit cost. The zone plan for this case suggests not to install any charging system in the rest of the zones, as they do not improve the energy delivery to cost ratio.

Introducing budget limits allows us to explore which additional zones can be added with this absolute optimal plan. This is analogous to having a certain range of budget, and then determining the best way to spend, achieving maximum return (in terms of energy delivery) from that expenditure. Gradually increasing budget ranges are presented in Table VI to observe how the optimal zone plans change. With a budget of \$1-2 million, two more zones with 250 kW and another two with 125 kW systems were selected by the optimization. Similarly, as the budget range moved upwards, more and more zones were selected; the charging power determined by the energy delivery per unit cost and the budget limit. Finally, with no budget upper limit, it is possible to install the most expensive 250 kW charging system at all zones.

Performance of these zone plans obtained from the optimization are shown in Table VII. For the zone plans for each budget range, total energy delivered to the BETs are presented along

TABLE VII
PERFORMANCE OF DETERMINED ZONE PLANS

Budget Range (\$M)	Wireless Energy Delivery (MWh)	Energy Delivery per Unit Cost (MWh/\$M)	%Feasible Tours for BET Drayage Fleet
None	0	-	86%
No lower limit	13.3	24.0	88%
1-2	18.3	18.0	89%
2-3	23.2	11.6	89%
3-4	26.9	9.0	90%
4-5	28.8	7.2	90%
5-6	29.7	5.9	91%
No upper limit	30.9	5.1	91%

with the energy delivery per unit cost. Additionally, the effect of installing wireless charging zones according to the optimal plans on the BET drayage fleet operation is also provided. This provides additional perspective in determining the effectiveness of the zone plans by demonstrating the extent to which the intended users are benefiting. On top of the budget ranges shown in Table VI, the case with no wireless chargers installed is shown as a baseline to illustrate the improvement in BET fleet tour completion with range extension from wireless charging. For our studied fleet, with no wireless charging, 86% of the

193 tours would be completed. This value increased as more budget was sanctioned for installing wireless charging zones, as trucks received more energy to replenish their batteries; this can be seen from the amount of energy delivery of wireless chargers shown in the 2nd column. The 3rd column shows the amount of energy delivered per unit cost of installation. This value is the highest for the case with no lower budget limit as for this scenario, the absolute best zone plan was attained. This value decreases with increasing budget range. This is because the lower budget ranges had the more efficient zones already selected (higher truck presence and smaller length). As the budget increases, less efficient zones had to be selected, and the energy delivery amount per unit cost decreased. However, even though the energy yield per unit cost decreases, the delivered energy increases, contributing to making more tours feasible for the BET fleet.

For our studied fleet activity, the budget range of \$3-4 million is probably the best middle ground. It increases fleet tour feasibility by 4%, compared to the case with no wireless charging. The higher budget ranges only yield limited gains. However, it should be noted that these results are obtained from a small sample set, and applying the methodology developed in this paper to a larger data set can provide further insight into wireless charging zone planning at ports for drayage operation. This study highlights the capability of economic wireless charging schemes at ports to effectively address range anxiety of drayage BETs. Wireless charging can be considered as a viable tool to entice drayage fleets into adopting BETs, even for a portion of their fleet, and thus aiding the port operators in reducing emissions. As further incentive, relevant agencies may also consider subsidizing the cost of installing wireless charging receiver on BETs, and creating dedicated charging lanes at terminal gates.

Comparing the feasible tour percentage from Tables V and VII, we can see that 90% completion can be achieved by either installing 125 kW systems in all zones, or installing according to the optimal zone plan for \$3-4M – which suggests installing 250 kW systems in select zones (Table VI). Similarly, 91% completion can be achieved by either installing 250 kW systems in all zones, or a mix of 125 kW and 250 kW systems in specific zones (optimal plan for \$5-6M). This highlights the efficacy of the optimization to extract the best performing plans.

The results from Table V and Table VII also showed that even after installing the higher-powered system at all the wireless charging zones, the BET drayage fleet failed to complete all the tours. The single tour beyond BET range (as shown in Fig. 4) contributed to this. Additionally, even with wireless charging at port and opportunity charging at home base combined, some trucks were not recharged enough to carry out some tours. These ultimately resulted in a maximum of 91% tour completion with the simulated fleet operating BETs with 565 kWh batteries and rated charging power of 250 kW. Higher capacity batteries, ability to charge at higher powers, and additional in-tour charging are some options that can aid in fulfilling the tours remaining infeasible.

IV. CONCLUSION

In this paper, wireless charging at port locations as a means of range extension of battery electric drayage trucks has been studied. An optimization problem has been formulated for optimal planning of wireless charging zones to identify zones and corresponding charging powers that provide the maximum charging energy per unit cost. The formulated optimization problem has been solved using genetic algorithm as it is well-suited for such optimization. The obtained optimal zone plans were evaluated by simulating a BET drayage fleet, where each truck's energy demand was estimated using a microscopic energy consumption model. The results show wireless charging's efficacy in improving BET fleet performance through range extension, and the capability of optimal zone planning to produce plans that provide the best charging performance within specific budget limits. Depending on the budget allocated for installing wireless charging systems, tour completion can be increased by 2%-5%, and optimal plans can achieve similar performance as naive plans without installing charging systems in all zones. The results presented in this paper are based on a small number of drayage truck samples at the ports of Los Angeles and Long Beach. The results can be improved by using data from a larger number of drayage trucks from several drayage fleets serving the ports. In addition to that, the costs incurred by drayage operators for wireless charging is not studied in this paper. The authors intend to investigate these in a future work.

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