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 thisapplication. In this paper, wireless chargingat 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 of20 BETs from a drayageoperator serving the ports of Los Angeles and Long Beach, using a microscopic BET energyconsumption 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 chargingsystems, and what levelof 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.

*llldex Te*mis-Class 8 truck, drayageoperations, 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 [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 becomingavailable [3], [4], the range of these BETs are still not enough for all freight applications, especially the ones over longdistances.The current BETs make moresense whenconsidered forshorter-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 byheavy-duty trucksin-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 ofdrayage 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 notshared 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 besuitable for increasingly more applications. Their comparative study of BETs with hybrid trucks showed that BETs were more effective in reducing air toxins. They also

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suggested investment in charging infrastructureto promote BET use [7]. Ramirez-Ibarra andSaphores tackled thecost issue of replacing thediesel drayage trucks withzeroemission 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 yetas a previous studyrevealed thata BETfleet isincapable 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 fordiesel trucks, thatdowntime 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 forport 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 tostationary 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 ona 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], catswarm 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 ill. 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 theselected zones, considering budget constraints. A BET model, and a fleet operation framework wereformulated 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 theSan Pedro Bay portcomplex (Port of Los Angeles and Port of Long Beach), the Inland Empire area, and the Greater Los Angeles Metropolitan area. Occasional service destinations

TABLE!
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 170engine control unit (ECU) parameters and GPS data (e.g., speed, timestamp, latitude, longitude) at 1 Hz. The collected truck activity data wassegmented in terms of trips, which was later used toidentify tours. Trip was defined as travelling between two nodes, while tour represented a chain of trips starting from the base and finally returningtoit.Thedata extracted from thelogger 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 (flatterrain).The finaldataset 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.Todo this,firstthe port terminals at thecomplex wereidentified(Fig.1).Then, using theactivity 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.Thestop/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 changingeven when the trucks werestationary (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 chargingevents, assuming those zones tohave 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 totruck j inzonei during eachsecond, twas calculated as:

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

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:

$$E^{WChrg}_{i} = \sum_{j=1}^{m} P^{WChrg}_{i,j} T_j \quad (2)$$

where T_i is the total amount of time (in seconds) truck j spent in zone i, and mis 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 $U_{P_{WC}}$ is the unit cost per mile for installing wireless charging syste . This unit cost, $U_{P_{WC}}$, depends on the rated charging power selected for zone i, P_{WC_i}.

Itcan beseen from Table III that all 23 zones were not visited byeach 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

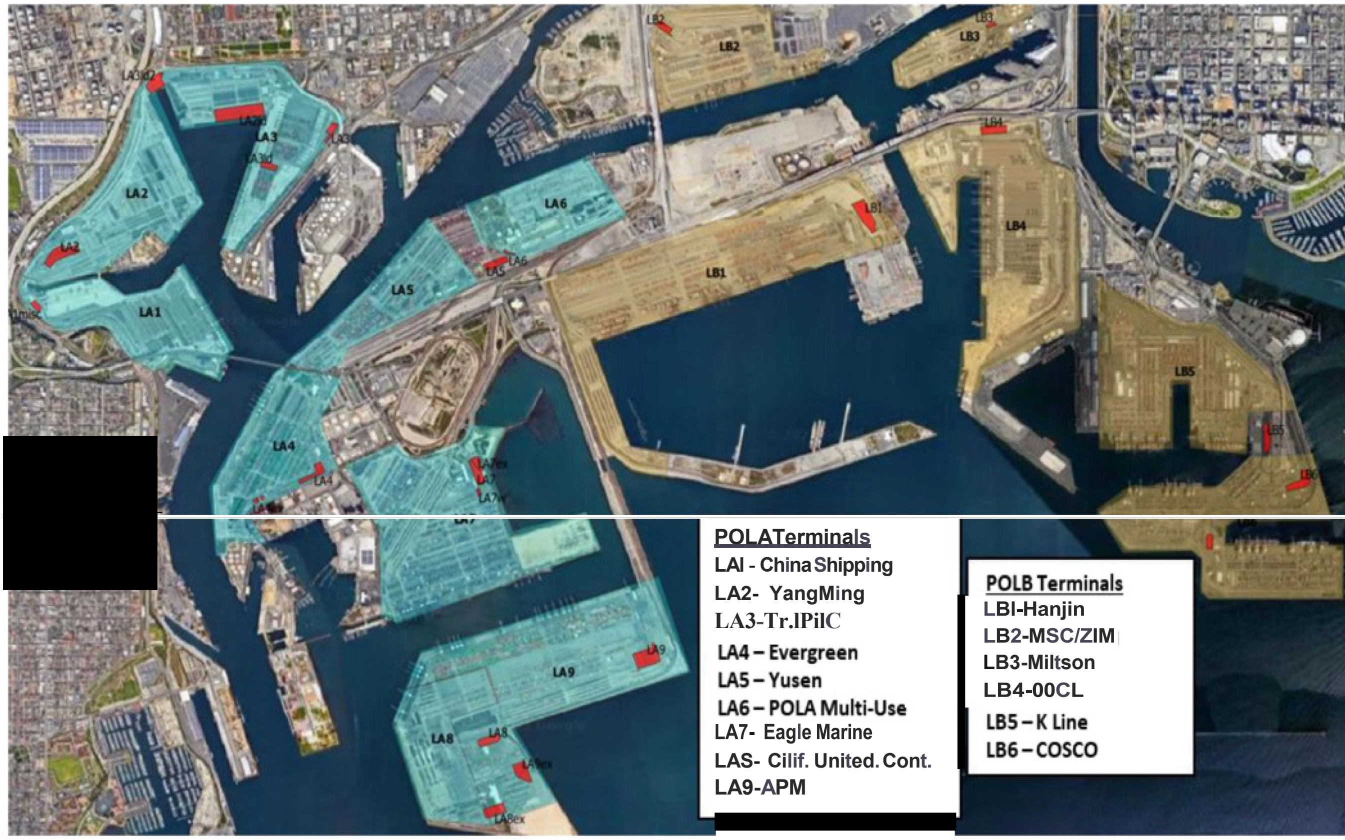

Fig. l. Locations identified to place wireless chargers (in red) at different terminals (marked by translucent turquoise and brown polygons) at the Port of Los Angeles (POLA) and the Port of Long Beach (POLB).

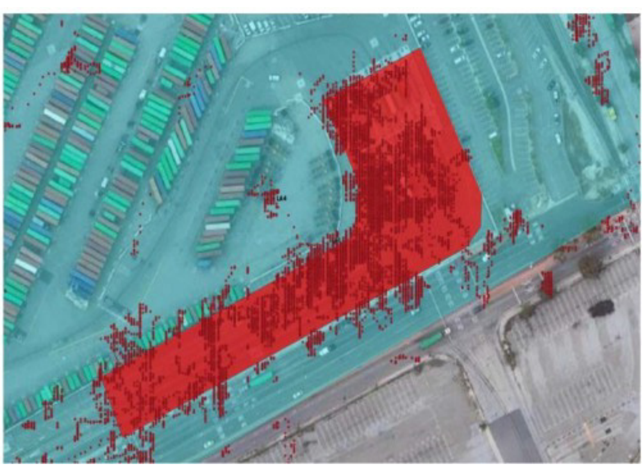

Fig. 2. Identifying truck presence (red dots) in a potential wireless charging zone (red polygon).

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, andsome zones the lower-powered one. The same budget cap could bemet with differentsuch selections. Depending on the selected zones, some selections (e.g., more total truck presence with less total roadway length to cover) coulddeliver moreenergy to thetrucksthanothers(e.g.,lesstotal 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-poweredsystem 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 maximumamountof energy delivery per unitamount 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:

$$\text{Objective Function} = \sum_{i=1}^{n} E_{Chrg} \Big/ \sum_{i=1}^{n} C_i. \qquad (4)$$

TABLE ill
WIRELESS CHARGING STfJISTICS

Operating houn	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/fruck ID	LLOS2	LLOS6	PEN016	TEC004	TEC006	TEC02S	TEC031	TEC042	TEC043	TEC04•	TEC04'	TEC04	TEC047	TEC048	TEC049	TEC0S0	Sum
LB6	550	194	0	253	0	0	3567	1406	64	1911	1013	0	99	0	0	0	9057
LB6m.isc	229	0	0	6	0	0	917	0	1532	0	1088	0	0	721	0	0	4493
LAS	3	2187	5285	(I	C	(I	(I	C	(I	3982	611	(	397	(I	(I	164	12629
LA9	4790	0	3122	0	7933	12574	7770	0	6252	2763	3021	7649	9070	4324	7273	4574	81115
LA8ex	95	C	642	(I	647	286	3789	C	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	IS	2889	2456	1422	26520
LA31d2	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	SI	0	288	823	39	6	34	0	207	0	0	10007
LA31d	324	174	2354	997	1755	724	0	318	0	153	0	650	0	199	0	0	7648
LA21d	182	0	4	S2	3529	0	0	4406	3420	0	0	0	0	0	0	3861	15454
LBl	0	5953	789	0									0	1418	6192	4309	29495
LB	I	556	u	2818	2666	2248	929		400	292	2237		22	u	364	206	12945
ILA/W	I	I	.l't'TV	/',II	1948	449	1935	3024	32 81	1!UH	[illegible]	0	l	,,J,	/O/	LU',/	)1500
LB	0		0	0	0	1127	92		0	0	703		97		0	0	2019
LAS	0	0	0	0	0	0	228	0	• 0	0	151	0	0	205	0	601	1185
ILH	I	I	u	u		u	lo ,	.l'tJ	u	l	u	l	l	14/ 1	u	IIU.I	DOJO
LA2	0	0	0	0	0	0	0	183	0	201							
LAlm.isc	(	C	(I	(I	C	(I	(I	C	(I	IC							
Sum	17263	16400	35771	33436	43288	28706	31585	30868	44757	28005							
¾of operating time	13	8	12	14	18	22	15	13	17	15							

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

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

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

The optimization problem can then be formulated as:

$$\text{maximize}\ \ f\,(Pwc)\ . \tag{6}$$

$$\text{subject to}\ \sum_{i=1}^{n} L_i u_{Pwc_i} \leq \text{budget} \tag{7}$$

To simplify the optimization problem, we considered three choicesof rated charging power foreachof *then* zones, as OkW, 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* $l.9M/mile cost was considered for the 125**kW**charging system, as *it* isclosest to the charging power of the $1.9M/mile system. The other charging power of 250**kW** was assumed tocost 1.5times higher, $2.85M, considering some costsaving due toeconomy of scale. This was purely based on assumption, as no data was available. The cost for O 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 *Gib* as the lower bound and *Cub* as the upper bound. With these considerations, the optimization problem can be expressed as:

$$\text{maximize}\ f\,(Pwc) \tag{8}$$

$$\text{subject to}\ Gib \leq \sum_{i=1}^{n} L_i U_{Pwc_i} \leq Cub \tag{9}$$

$$Pwc_i \in \{0,\ 125{,}250\},\ i = 1,\ \ldots\ ,\ n \tag{10}$$

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 ($-\ f(Pwc)$); minimizing $-\ f(Pwc)$ means maximizing $f(Pw_0)$. 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. BETModel

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 tasksrecorded in thecollected 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 $E_t^{Battery}$ isbattery energy consumption in each second; E_t^{Tract}, E_t^{Acc}, E_t^{Regen} and E_t^{WChrg} areinstantaneous tractive energy consumption, accessory load consumption, energy regeneration from braking, andenergygainfrom wireless charging, respectively. E_t^{WChrg} wasobtained using(2). The rest were derived as:

$$E_t^{Tract} = \frac{P_t T}{\eta_{T/W}\eta_{T/Fd}\eta_{T/M}\eta_{T/B}};\ \forall (P_t \geq 0) \quad (12)$$

$$P_t = m v_t a_t + 0.5\rho C_d A v_t^2 + C_{rr} m g v_t \cos\theta + m g v_t \sin\theta \quad (13)$$

where m is BET mass, v_t is instantaneous speed, a_t is instantaneous acceleration $(a_t = v_{t+1} - v_t)$, ρ is airdensity, 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; $\eta_{T/W}, \eta_{T/Fd}, \eta_{T/M}, \eta_{T/B}$ are efficiencies of wheel, final drive, motor, and battery, respectively. P_t gives tractive powerconsumption in each second, which is used in (12) to get the tractive energy consumption, considering $T = 1$ as the data is 1 Hz. $\eta_{T/B}$ wascalibrated for matching thesimulated 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 $T = 1$.

$$E_t^{Regen} = P_t T \eta_{T/W}\eta_{T/Fd}\eta_{T/M}\eta_{T/B};\ \forall (A < 0) \cap (v_t > 5) \cap (a_t < 3) \quad (15)$$

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 tripstarted and ended at

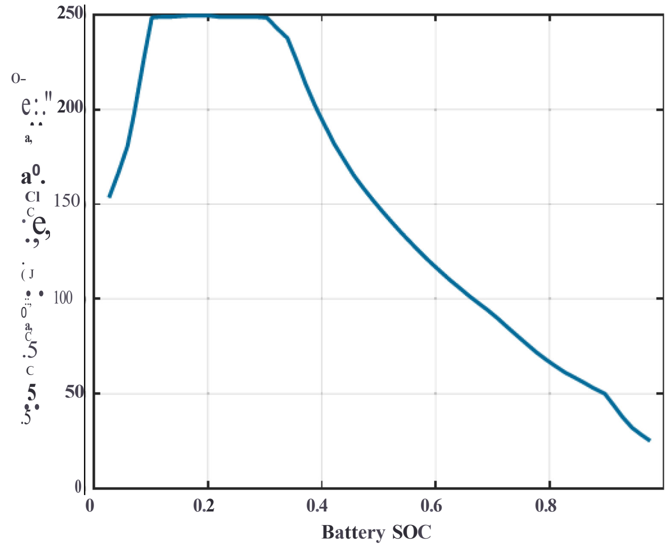

Fig. 3. Battery SOC-dependent charging power assumed for BET charging at base.

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 toursrequiring energy more than the batterycapacitycould 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 theBETs returned to the baseat theend 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-PP 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	*Cd*	0.65
	Front area (m^2)	*A*	8.5
	Coefficient of rolling resistance	*Crr*	0.008
	Accessory load for EV(kW)	PAcc	2.8
	Wheel efficiency	1'/w	0.99
	Final drive efficiency	1'/Fd	0.98
	Motor efficiency	I'JM	0.88
	Battery efficiency	I'JB	0.88
Atmosphere	Air density (kg/m^3)	ɒ	1.161
	Gravity (m/s^2)	*g*	9.8
Wireless Charging	Rated charging power(kW)	Pwc	0, 125, 250
	Wireless charging efficiency	1/wc	0.9
	Per mile cost ($M)	UPwc	0, 1.9, 2.85
Base Charging	Rated charging power(kW)	-	250
	Charging efficiency	1/c	0.85
	Effective time factor	*a*	0.8

TABLEV
FEASIBLE TOURS UNDER DIFFERENT SCENARIOS

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

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

IIL 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 the125kW system achieves 4% improvement. The distribution of individual tour battery depletion for twocases: no wireless charging, and 250 kW wireless charging at all zones,

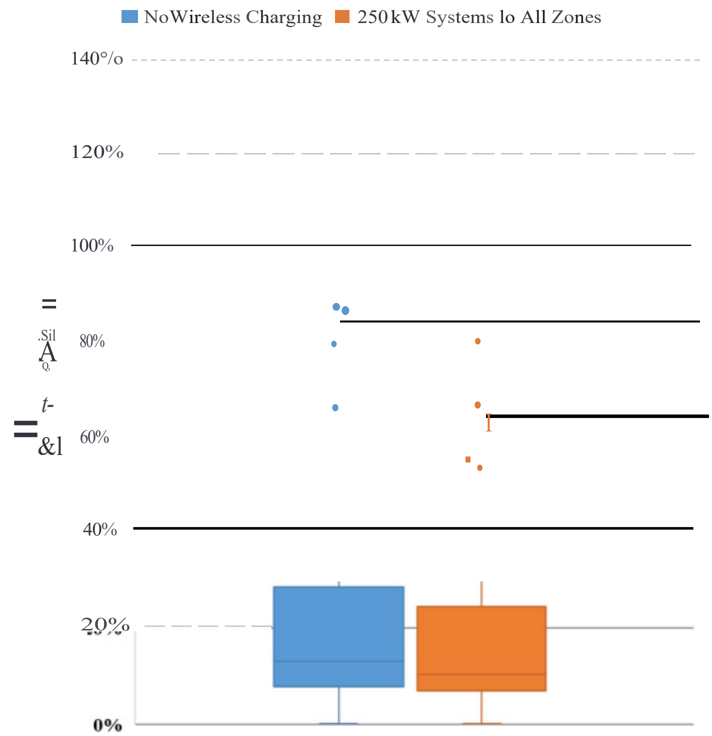

Fig.4. Distribution of battery depletion, shown as box plots. One specific tour depleted the battery 125% for bothcases, indicating that this tour is out of range for the simulated BET, and it did not visit any wireless charging zone.

are shown in Fig. 4. Tours passing through wireless charging zones allowed batteries tobecharged, thus thecase 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 zonelengthsarealso presented witha color codein thistable. The colors show relative values (red: lowest, green: highest). Solving theformulated optimization problem givesoptimal 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)	Chari?in Power at Zones (kWI						
			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
LBl	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
LA21d	15454	**0.22**	0	0	0	0	0	250	250
LB4	12945	0.11	0	0	0	250	250	250	250
LAS	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
LA31d	7648	0.o7	0	0	125	0	250	250	250
LBS	**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
LAlmisc	**714**	**0.04**	0	0	0	0	125	0	250

This plan called for installing the 250 kWcharging system at the two zones having the most truck presence, and relatively smaller lengths (can beseenfromthecolors). 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 bow 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 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

TABLE VII
PERFORMANCE OF DETERMINED ZONE PLANS

Budget Range (SM)	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 unner limit	30.9	5.1	91%

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 tomaking 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 dataset can provide further insight intowireless charging zone planning at ports for drayage operation. This study highlights the capability of economic wireless charging schemes at ports toeffectively 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 considersubsidizing thecostof 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 (fable 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 Vand Table VII alsoshowed 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 outsome 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 chargingenergy per unitcost.Theformulated optimization problem bas been solved using genetic algorithm as it is well-suited for such optimization. The obtained optimal zone plans were evaluated by simulating a BETdrayage fleet, whereeach truck's energy demand was estimated using a microscopic energy consumption model.Theresultsshow wireless cbarging'sefficacy 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 planscanachievesimilar performance as nai"ve 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 notstudied in this paper. The authors intend to investigate these in a future work.

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REFERENCES

[11 H. Liimatainen, O. van Vliet, and D. Aplyn, "The potential of electric trucks-An international commodity-level analysis," *Appl. E11ergy,* vol. 236, pp. 804-814, 2019, doi: I0.1016/j.apenergy.2018.12.017.

[21 B.Nykvistand0. Olsson,"The feasibility of heavy batteryelectrictrucks," *Joule,* vol. 5, no. 4, pp. 901-913, 2021, doi: I0.1016/j.joule.2021.03.007.

[3] "VNR electric series," Accessed: Apr. 23, 2022. [Online]. Available: https://www.volvotrucks.ca/-/media/vtna/files/en-us/5631_volvo_vnr-electric-brochure_compressed-for-web_f-update.pdf?rev I&hash= 0DD967A6FD553224B98281IB11865B39</bib>

[4] D. T. N. A. LLC, "eCascadia," Accessed: Apr. 25, 2022.[Online]. Available: https://freightliner.com/trucks/ecascadia/

[5] "Drayage trucks at seaports & railyards," Accessed: Apr. 25, 2022. [Online]. Available: https://ww2.arb.ca.gov/our-work/programs/drayage-trucks-seaports-railyards

[6] S. I. Youand S. G. Ritchie, "A GPSdata processingframework for analysis of drayagetruck tours," *KSCEJ. Civil E11g.,* vol. 22, pp. 1454-1465, 2_018.

[7] G. Giuliano, M. Dessouky, S. Dexter, J. Fang, S. Hu, and M. Miller, "Heavy-duty trucks: The challenge of getting to zero," *Transp. Res. Part D Tra11sp. EtlViron.,* vol. 93, 2021, Art. no. 102742.

[8] M. Ramirez-Ibarra and J.-D. M. Saphores, "Health and equity impacts from electrifying drayage trucks," *Tra11sp. Res. Part D Transp. E11viro11.,* vol. I16, 2023, Art. no. 103616.

[9] S. Tanvir, F.Un-Noor, K. Boriboonsomsin,and Z. Gao,"Feasibility of operating a heavy-duty battery electric truck fleet for drayage applications," *Transp. Res. Rec.,* vol. 2675, no. I, pp. 258--268, 2021.

[1OJ California AirResources Board, "LCTI: Portof los angeles'shore tostore' project," Accessed: Sep. 12, 2023. [Online]. Available: https://ww2.arb.ca.gov/lcti-port-los-angeles-shore-store-project

[11J California Air Resources Board, "LCTI: Zero emissions for califomia ports (ZECAP)," Accessed: Sep. 12, 2023. [Online]. Available: https://ww2.arb.ca.gov/lcti-zero-emissions-califomia-ports-zecap

[12) G. Di Uio, P. Di Giorgio, L. Tribioli, V. Cigolotti, G. Bella, and E. Jannelli, "Assessment of a hydrogen-fueled heavy-duty yard truck for roll-on and roll-off port operations," SAE, Warrendale, PA, USA, Tech. Rep. 2021-24-0109, 2021.

[13) Y. Alwesabi, Z. Liu, S. Kwon, and Y. Wang, "A novel integration of scheduling and dynamic wireless charging planning models of battery electric buses," *Energy,* vol. 230, 2021, Art. no. 120806.

[14] F. Un-Noor, A. Vu, S. Tanvir, Z. Gao, M. Barth, and K. Boriboonsomsin, "Range extension of battery electric trucks in drayage operations with wirelessopportunity charging at port tenninals," in *Proc. IEEEVeh. Power Propulsion Conj.,*2022, pp. 1---o.

[15] Z.Chen, Y.Yin,and Z. Song,"A cost-competitiveness analysis ofcharging infrastructure for electric bus operations," *Transp. Res. Part C Emerg. Technol.,* vol. 93, pp. 351-366, 2018, doi: 10.1016/j.trc.2018.06.006.

[16] Z. Liu and Z. Song, "Robust planning of dynamic wireless charging infrastructure for battery electric buses," *Transp. Res. Part C Emerg. Tech11ol.,* vol. 83, pp. 77-103, 2017, doi: 10.1016/j.trc.2017.07.013.

[17] Z. Bi, 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," *Appl. Energy,* vol. 146, pp. 11-19, 2015, doi: I0.1016/j.apenergy.2015.02.03l.

[18] Z. Liu, Z. Song, and Y. He, "Optimal deployment of dynamic wireless chargingfacilities for an electric bus system,"*Transp. Res. Rec.,* vol. 2647, no. l,pp. 100---108,2017.

[19] X. Wu, D. Freese, A. Cabrera, and W. A. Kitch,"Electric vehicles' energy consumption measurement and estimation," *Transp. Res. Part D Tra11Sp. Environ.,* vol. 34, pp. 52---07, 2015,doi: 10.1016/j.trd.2014.10.007.

[20] C. De Cauwer, J. Van Mierlo, and T. Coosemans, "Energy consumption prediction forelectric vehicles basedon real-world data," *Energies,* vol.8, no. 8, 2015, Art. no. 115408, doi: 10.3390/en8088573.

[21] Z. Gao, Z. Lin, and0. Franzese, "Energy consumption and cost savings of truck electrification for heavy-duty vehicle applications;• *Transp. Res. Rec.,* vol. 2628, no. I, pp. 99-109, 2017, doi: 10.3141/2628-11.

[22] Z. Gao, Z. Lin, S. C. Davis, and A. K. Birky, "Quantitative evaluation of MD/HD vehicle electrification using statistical data," *Transp. Res. Rec.,* vol. 2672, no. 24, pp. 109-121, 2018, doi: 10.1177/0361198118792329.

[23] P. Ruan, G. Wu, Z. Wei, and M. J. Barth, "A modularized electric vehicle model-in-the-loop simulation for transportation electrification modeling and analysis," in *Proc. IEEE Int. Intell. TrallSp. Syst. Conj.,* 2021, pp. 1685-1690.

[24] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, and I. khan, "Optimal location of electric vehicle charging station and its impact on distribution network: A review," *Energy Rep.,* vol. 8, pp. 2314--2333, 2022, doi: 10.1016/j.egyr.2022.01.180.

[25] L. Chen, C. Xu, H. Song, and K. Jermsittiparsert, "Optimal sizing and sitting of EVCS in the distribution system using metaheuristics: A case study," *Energy Rep.,* vol. 7, pp. 208--217, 2021, doi: 10.1016/j.egyr.2020.12.032.

[26] S. Deb, X.-Z. Gao, K.Tammi, K. Kalita,and P.Mahanta, "A novel chicken swarm and teachinglearning based algorithm for electric vehicle charging station placement problem," *Energy,* vol. 220, 2021, Art. no. 119645.

[27] P. Tadayon-Roody, M. Ramezani, and H. Falaghi, "Multi-objective locating of electric vehicle charging stations considering travel comfort in urban transportation system," */ET Ge11er., Tra11smiss. Distrib.,* vol. 15, no.5,pp.960--971,2021.

[28] A. Datta and D. Sengupta, "Renewable energy supported bi-directional electric-vehicle charging station allocation in distribution network using INBPSO technique," *Int. J. Renewable Energy Res.,* vol. 11, no. 2, pp.750--761, 2021.

[29] P. Rajesh and F. H. Shajin, "Optimal allocation of EV charging spots and capacitors in distribution network improving voltage and power loss by quantum-behaved and Gaussian mutational dragonfly algorithm (QGDA)," *Electric Power Syst. Res.,* vol. 194, 2021, Art. no. 107049.

[30] L. Liu, F. Xie, Z. Huang, and M. Wang, "Multi-objective coordinated optimal allocation of DG and evcss based on the V2G mode," *Processes,* vol. 9, no. 1, 2020, Art. no. 18.

[31J J. Li, Z. Liu,and X. Wang,"Public chargingstation location determination forelectric ride-hailing vehicles based on an improved genetic algorithm," *Sustain. Cities Soc.,* vol. 74, 2021, Art. no. 103181.

[32] G. Scora et al., "Variability in real-world activity patterns of heavy-duty vehicles by *vocation,"Tra11Sp. Res. Rec.,* vol.2673, no.9, pp. 51---ol, 2019.

[33] "Accelerating theEVtransition atthe portof Los Angeles,"2022. [Online]. Available: https://waveipt.wpengine.com/ports/

[34] G. Kay, "A I-mile stretch of road is being built in Detroit that can charge electric cars as they drive-If owners install a special receiver," 2022. Accessed: Jul.16,2022.[Online]. Available: https://www.businessinsider.com/public-road-detroit-to-charge-electric-cars-as-they-drive-2022-2

[35] M. Kane, "ElectReon completes dynamic wireless charging road for trucks," *I11sideEVs,* 2021. Accessed: Jul. 16, 2022. [Online]. Available: https://insideevs.com/news/481997/electreon-completes-dynamic-wireless-charging- road-trucks/

[36] Electreon,"Electreon announcesextension of world's firstwirelesselectric road for trucks and buses," 2022. Accessed: Jul. 16, 2022. [Online]. Available: https://electreon.com/articles/electreon-announces-extension-of-worlds-ti rst-wireless-electric- road-for-trucks-and-buses

[37] I. The MathWorks, "ga," Accessed: Jul. 17, 2022. [Online]. Available: https://www.mathworks.com/help/gads/ga.html?s_tid=mwa_osa_a

[38] "Tapered charging," Accessed: Apr. 24, 2022. [Online]. Available: https://teslatap.com/articles/supercharger-superguide/

[39] L. Soares and H. Wang, "A study on renewed perspectives of electrified road for wireless power transfer of electric vehicles," *Renewable Sustain. Energy Rev.,* vol. 158, 2022, Art. no. 112110.

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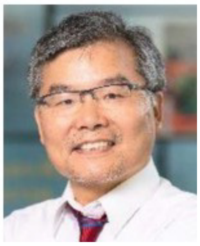

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