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Range Extension of Battery Electric Trucks in Drayage Operations with Wireless Opportunity Charging at Port Terminals

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***Abstract*—Class-8 battery electric trucks (BET) are modeled and simulated in this paper to determine their capability in fulfilling real-world drayage activity under different operational scenarios. Potential wireless charging zones at port terminals are identified, and wireless charging opportunities are introduced to improve drayage activity fulfillment of BETs. The results show that current BETs would be able to fulfill approximately 79-86% of the real-world drayage activity sample used in this research, and that the ability to receive wireless opportunity charging at port terminals could help increase the activity fulfillment to about 84-91%.**

Keywords*—*electric vehicle, class-8 truck, range anxiety, drayage operations, fleet, wireless charging

I. 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 (BET) have long been questioned. With the recent advances in battery technology, and in electric vehicles (EV) 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], and more are 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 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 near-by 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, as the frequent base visits can be used for charging, the limited mileage addresses electric range anxiety, and the frequent braking and slow-speed movement favor BETs over diesel trucks by providing 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 have a strong case to replace the diesel trucks in drayage fleets.

Energy demands in drayage operation along with the service schedule need to be analyzed to properly assess BET deployment feasibility for this application. A model BET can be simulated to carry out recorded drayage activity from diesel trucks to investigate its capability. Energy consumption of EVs based on activity is well-investigated. The physics governing vehicle energy demand based on driving speed was modeled in [5]. Reference [6] used similar formulations for energy consumption prediction. In [7], heavy-duty battery electric and plug-in hybrid vehicles were modeled. Similar modeling approach was followed in [8] to evaluate performance of different medium- and heavy-duty EVs. Reference [9] also demonstrated EV energy consumption formulation in detail. In this paper, following similar procedures, a microscopic energy consumption model is developed to mimic a commercial BET with two different battery capacities.

For simulating charging scenarios, assumptions are made to emulate real-world conditions (e.g., lost time for setting up charger). Tanvir et al. demonstrated methodology to

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characterize drayage truck activity data into trips (travelling between two nodes) and tours (a chain of trips starting at the base and finally coming back to it) [4]. Such identification is necessary to break up the microscopic energy consumption data into individual sessions, and to identify potential time durations for charging. This methodology is adopted in this paper to analyze real-world drayage fleet activity data. Finally, drayage fleet operation was analyzed for three scenarios, each with distinct properties, to investigate if a BET drayage fleet can perform at the same level as the diesel fleet.

Failing to sufficiently recharge the batteries would be 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 250 kWh battery would be able to perform 75% of the tours if base charging between tours was considered [4]. In this paper, it is investigated if the modeled trucks with larger batteries, and slightly higher charging power—albeit under more realistic conditions—can help improve this number. Additionally, as a convenient and accessible solution for out-of-base charging, this paper proposes wireless charging at port locations where drayage trucks spend considerable amounts of time. This additional charging opportunity can further help increase the proportion of tours that are feasible. Installing wireless chargers at ports can benefit both drayage operators and the port authority [11]. 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 while scheduling the tours. Wireless charging mitigates this issue as well. The port authority benefits from the operators opting to increase BET penetration in fleets, reducing emissions and thus meeting port objectives [10]. This paper contributes through its simulation of current BETs for drayage application, identification of wireless charging zones at port terminals, and studying their effect on BET drayage operation.

II. Methodology

A. 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 (Port of Los Angeles and Port of Long Beach), 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 (ECU) parameters and GPS data (e.g., timestamp, speed, longitude, latitude) were recorded at 1 Hz with data loggers. The collected data was then processed in multiple steps for data cleaning and correction, identifying trips, and trip origin-destination cloaking for confidentiality [12]. Road grade data was 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, Jan 23, 2017 through Friday, Jan 27, 2017.

B. Tractive Energy Consumption Model

Using the 1 Hz activity data, 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, 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 considering the component efficiencies:

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

where $\eta_W, \eta_{Fd}, \eta_M, \eta_B$ 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 lbs).

Negative P_t instances (deceleration) at certain thresholds of speed and acceleration provided regeneration [7]:

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

C. Wireless Charging Model

The BETs were considered to charge wirelessly at out-of-base locations, wherever wireless chargers would be available. Placement of wireless chargers need 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, as this would allow the trucks the most opportunity for charging. To identify these locations, different terminals at the port complex were identified first (Fig. 1). Collected truck activity data was 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 this, vehicle activity data was 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 was used to identify instances of truck presence at any of the potential charging zones. Noisy GPS data showing position change when vehicles were not moving were corrected. This was done by considering a vehicle staying in a charging zone when its speed is zero, but GPS data showing 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 Table I. 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:

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

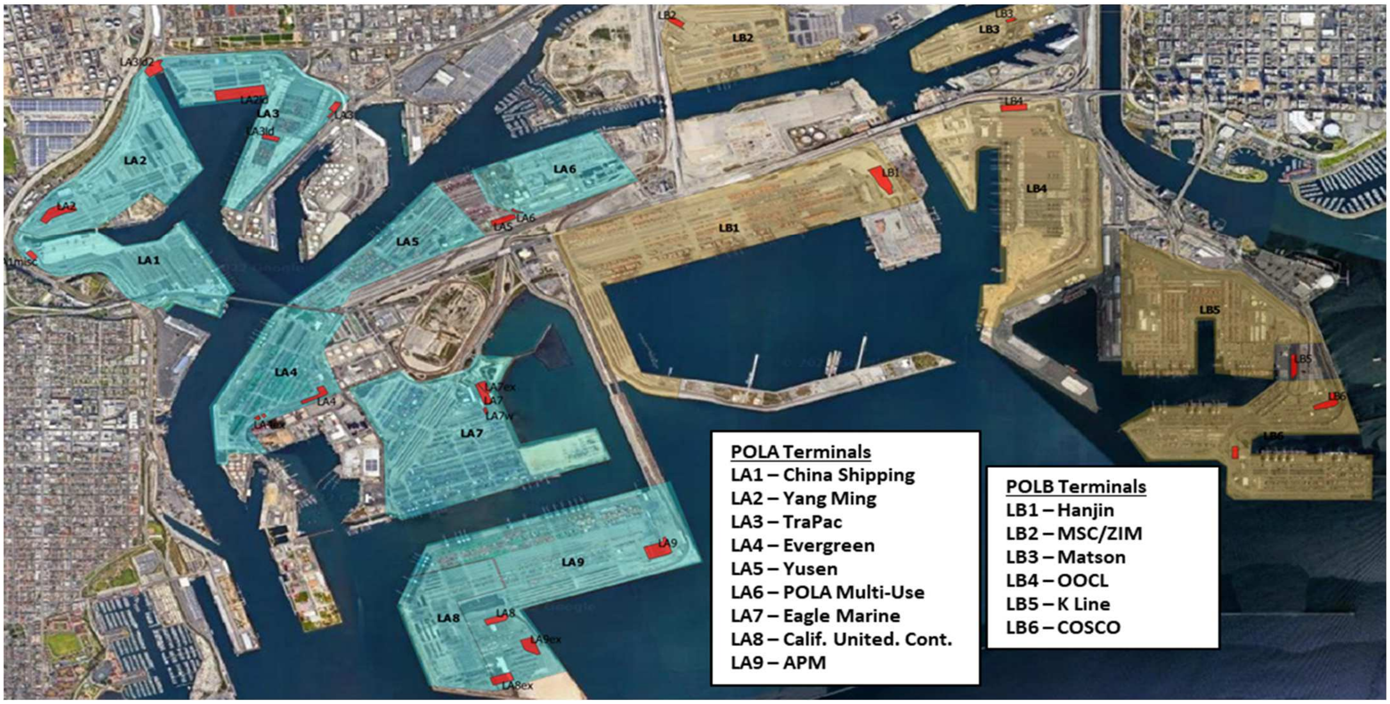

Fig. 1. Locations identified to place wireless chargers (in red) at different terminals (marked by translucent torquise and brown polygons) at the Port of Los Angeles (POLA) and the Port of Long Beach (POLB).

TABLE I. WIRELESS CHARGING STATISTICS. COLORS SHOW RELATIVE VALUES (RED: LOWEST, GREEN: HIGHEST) FOR TIME SPENT AT EACH ZONE

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*

D. Tour Generation

The trip energy consumption, and other trip-level data was 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 [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:

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

E. Base Charging Model

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

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

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 state of charge (SOC: energy content of the battery as a fraction of battery capacity); SOC-P_t^C curve is shown in Fig. 2 [13]. 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 in setting up trucks at charger, the truck engaged in other tasks, or operators simply forgetting to plug in immediately. Table II shows parameters values for this study.

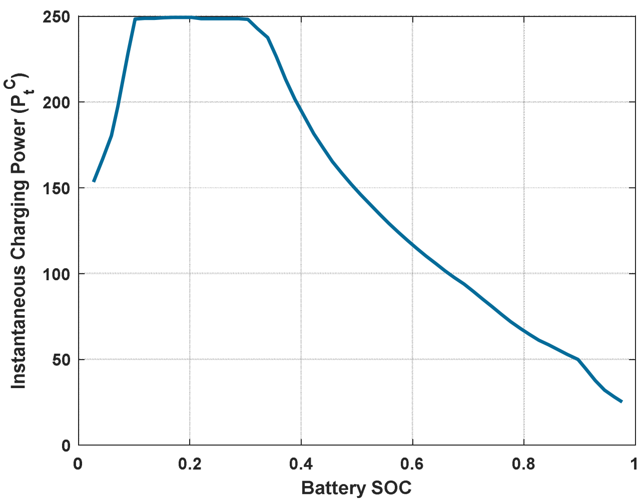

Fig. 2. Change of instantaneous charging power with battery SOC.

TABLE II. PARAMETER VALUES [1], [4][11][14]

	Parameter	Symbol	Value
Vehicle	Battery size (kWh)	-	377, 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	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

III. OPERATIONAL FEASIBILITY ANALYSIS

The modeled system was used to simulate several different scenarios to determine the operational feasibility of BETs. The scenarios are first described for a case where 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.

A. S-1: All Tours Start with 100% SOC

The first step to 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), estimated from the energy consumption observed from standard driving cycles [15]. 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 Eq. (1)-(7). This scenario assumes that the trucks start with a full battery at the beginning of each tour, and with this assumption, it was found that 4.1% and 0.5% 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 as the time spent at 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, we need to further analyze the tours determined to be feasible in S-1 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, skipping a few.

B. S-2: Base Charging on Rest Day

The collected data showed that the studied fleet operated six days a week, with Sunday as the rest day. As the drayage tours are scheduled beforehand, the operator would keep the rest day for charging the trucks. So, 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 goes through the scheduled tours with $E^{ChargedBattery}$ (from Eq. (8)) until the batteries are depleted. Here, Eq. (1)-(8) were used; (8) being 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% and 81% would be feasible with 377 kWh and 565 kWh battery capacities, respectively.

C. *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 would be used to charge the trucks. Thus, this automatically includes the charging on rest day. Eq. (1)-(7) gave the tour energy consumption, 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% and 86% of the tours within ranges of 377 kWh and 565 kWh battery packs would be 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 as they are rated for 250 kW [1].

D. *Adding Wireless Opportunity Charging at Port Terminals*

Another way to improve tour completion is to introduce wireless charging at the port terminals. Table III 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 III. 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 visible from the increase in the fraction of feasible tours from 95.9% without wireless charging to 97.9% with 125 kW wireless charging, and then to 98.4% 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 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 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. This makes the tour sequence in S-2 (and S-3) be 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 as 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 this 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 paper other than the construction of S-2 and S-3, but this is a powerful tool to improve the efficiency of BET fleets. S-2 for 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 tours plateaus 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 most amount 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 paper demonstrated the enhanced capabilities of the newer BETs with increased battery capacity, as all the feasibility percentages were high than the values reported in [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% BET fleet in drayage application.

IV. Conclusions and Future Work

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

This study also evaluates 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 would be able to fulfill up to 90% 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 them to make 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, as it may not be financially possible to install all of them at once. As shown in Table I, some zones were visited for longer duration 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 (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.

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