# En-Route Opportunity Charging for Heavy-Duty Battery Electric Trucks in Drayage Operations: Case Study at the Southern California Ports

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***Abstract*—This paper presents a data-driven methodology for analyzing the deployment of heavy-duty (HD) battery electric trucks (BETs) in drayage operations by providing them with en-route opportunity charging. The analysis makes use of real-world activity data of existing drayage trucks at the San Pedro Bay Ports in California. The methodology involves first identifying trip-and-tour patterns of the trucks as well as whether they are loaded or unloaded, and then simulating energy consumption of the BETs if they follow these trip-and-tour patterns. En-route opportunity charging scenarios at different locations were then modeled to determine the state-of-charge (SOC) profiles of two example BETs based on two different charging power levels. Results show that one of the BETs would only need opportunity charging at the home base in order to complete all of its trips over a simulated two-day period. On the other hand, the other BET would need not only opportunity charging at the home base, but also take advantage of en-route opportunity charging at loading/unloading stops and also extending the length of the stop time on one of its stops, which will consequently impact the schedule of the trips that follow. In addition, our results show that there was no significant improvement in the SOC when increasing the charging power level from 50 to 150 kilowatt (kW) at the home-base and at one of the stops for this truck. These results highlight the importance of providing BETs, even those in short-haul operations, with access to en-route charging opportunities in order to increase the deployment of BETs.**

***Index Terms*—Opportunity charging, battery electric trucks, drayage operations**

## I. INTRODUCTION

In 2019, the transportation sector was the largest source of global warming emissions (29% of all emissions) according to the Inventory of US greenhouse gas (GHG) emissions from the Environmental Protection Agency (EPA) [1]. The transportation sector is also responsible for pollutants found in the air, such as oxides of nitrogen (NOx) and particulate matter (PM), which cause health risks such as asthma, heart attacks, and cancer [2], [3]. In 2017, HD vehicles contributed to 16% of NOx emissions in the United States (US), despite being only 10% of vehicles on US roads [4]. This disparity is mostly because HD vehicles consume more fuel per mile (average miles traveled per gallon of fuel consumed for single-unit truck =7.5 miles per gallon vs. 24.1 for an average car [5]). They also travel more miles per year (HD trucks average 60,000 miles per year vs. 12,000 for an average car [5]). In California, on-road and off-road mobile sources are the largest contributor to NOx and GHG emissions. According to the California Air Resources Board (CARB), direct GHG emissions in California from mobile sources were approximately 40% in 2017 [6]. In 2021, this number increased to more than 50% [3]. In addition, NOx emissions from mobile sources in California in 2017 accounted for 80% of the total. Over the years, there have been several efforts to address emissions from the transportation sector, with transportation electrification being one of the most recent strategies. In February 2021, the American Council for an Energy-Efficient Economy (ACEEE) ranked California as the national leader, being the only state in the country that has adopted a target for statewide HD electric vehicle (EV) deployment, and also considering the impact of transportation on disadvantaged communities [7]. These targets to address climate change in California were set as an important step towards achieving carbon neutrality by 2045, and can be found in Executive Order N-79-20 issued in September 2020 [8]. This executive order targets:

- All in-state sales of new passenger cars and trucks to be zero-emission by 2035;
- All drayage trucks operating in the state to be zero-emission by 2035;
- All MD and HD vehicles operating in the state to be

zero-emission by 2045, where feasible; and

- All off-road vehicles and equipment to be zero-emission by 2035, where feasible.

To meet these targets, CARB estimates that electrifying the state's MD and HD sectors will be critical, and 157,000 chargers will be needed to support 180,000 MD and HD vehicles anticipated for 2030. Further, in January 2021, the California Energy Commission (CEC) assessed the EV charging infrastructure and key actions needed by 2030 mentioning the importance of supporting innovative charging solutions and to continue the modeling efforts to project the quantities, locations, and load curves of chargers needed to meet statewide travel demand, including for MD and HD vehicles [8]. CARB also described the importance of electrification efforts and charging strategies applied to MD and HD fleets, particularly for Class 8 drayage trucks. The ports of Los Angeles and Long Beach (usually called together the San Pedro Bay Ports), are the largest container shipping ports in the US, handling about 40% of the waterborne imported cargo into the nation [9]. Consequently, the California South Coast region and San Joaquin Valley suffer some of the worst air pollution in the nation mostly related to truck activity and drayage operations [6]. Thus, CARB and CEC clearly state that more research and more pilot studies are needed to address these issues. California needs to continue working on EV charging strategies, in particular as applied to HD vehicles to meet current climate targets. Thus, to investigate the potential of HD transportation electrification efforts in California, we:

- propose a data-driven methodology to identify trip-and-tour activity patterns for potential en-route opportunity charging of BETs in drayage operations at the San Pedro Bay ports,
- adapt BET energy efficiency in the current literature as applied to loaded and unloaded conditions, and
- simulate charging scenarios at different locations to determine SOC with and without en-route opportunity charging for example drayage trucks based on two different charging power levels.

This paper is organized as follows. First, related work is presented in Section II. Then, the methodology and dataset are described in Section III. Next, the results and discussion are provided in Section IV. Finally, the conclusions and future work are presented in Section V.

## II. Related Work

Opportunity charging can be understood as any opportunity that the EV has to charge its battery, including brief stops at traffic intersections or stops to load or unload passengers at a bus station [10], [11]. Usually, drayage trucks carry cargo containers from shipping ports to nearby distribution zones, and also return to home-base daily during operation [12]. Several researchers have identified the activity pattern of drayage operations, highlighting them as one of the best candidates for electrification. In [13] truck trips were analyzed, finding that less than 1% of drayage trucks completed more than 5 trips per shift, and on average a truck delivered 12 round trips per day. The paper also mentions that the trucks spend most of its time navigating to the port and dealing with cargo logistics (port access, loading, etc.), completing about 60 miles per day near-dock service [13]. In addition, drayage fleet efficiency has also been studied. In [14], a drayage operation planning approach that minimizes cost and maximizes productivity was presented to deal with port access restrictions by slot capacity availability. Their results showed that drayage activity productivity can be increased by 10-24% when port access capacity is increased by 30% [14]. Furthermore, drayage truck emissions have also been assessed over the years. In [15] a coordinated truck model was presented to reduce emissions from empty truck trips. Their results suggest that a collaborative truck appointment system is an effective tool to reduce emissions, but that a congestion management tool is also needed at ports [15]. Several studies have targeted zero-emission drayage operations in Southern California. In 2012, a report prepared from Gladstein for the South Coast Air Quality Management District (SCAQMD) highlighted the potential benefits of catenary-accessible hybrid trucks at the port of Los Angeles [16]. Developments moved forward, and in 2017 Siemens built a test "eHighway" in Carson, California, near the port of Long Beach. The system only had three freight trucks that can pair with the one mile long catenary system: a BET, a natural gas hybrid-electric truck, and a diesel-hybrid truck. The trucks were zero-emissions when connected to the catenary, and when the eHighway ended, the trucks returned to use their internal engine to drive the rest of the path [17]. In addition, in 2013, a report from CALSTART aimed to research, identify, and evaluate potential technologies to address drayage needs while achieving zero-emissions in the San Pedro Bay Ports [18]. This report was intended to specify the requirements that zero-emission trucks must meet in order to substitute conventional diesel trucks, emphasizing the importance of routing strategies to improve productivity [18]. In [19], depot charging load profiles were modeled for multiple scenarios considering fleet size and charging strategies. The authors concluded that the opportunity for a managed depot charging of HD trucks depends on their duty cycles, and that there is a high variance in fleet electrification outcomes depending on fleet vocation and grid conditions [19]. In [12], activity of drayage trucks in Southern California was analyzed to estimate the corresponding electric energy consumption and SOC of their batteries. Their results show that 85% of the tours could be served by electric trucks if there is opportunity charging at the home base during tours. Thus, based on the gaps found in the literature, we go one step further by proposing a data-driven model to identify trip-and-tour activity patterns for en-route opportunity charging using real-world data. Additionally we simulate charging scenarios at different locations, not only home-base as in previous work, to determine SOC at different power levels.

## III. METHODOLOGY

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

In this paper, activity data at the terminal regions of the ports of Long Beach and Los Angeles over 2 days (August 2-3, 2021) were analyzed for two selected trucks (Truck A and Truck B) as an initial step to assess the necessity of providing en-route opportunity charging. As shown in Figure 1, the data provided were pre-processed and filtered by terminal region and truckID. Additionally, the GPS date time differential was calculated to get the time gap between each timestamp. Thus, a cluster of data points on the map with large time elapsed between timestamps would mean a potential home-base or warehouse where the truck stopped to rest or to load or unload cargo. To isolate the stops and home-base clusters where the truck spent more time, an unsupervised k-means machine learning (ML) model was implemented in Python. The k-means algorithm clusters data by separating them in groups while minimizing the inertia [20]. This algorithm has been widely used across a range of applications mostly because its scalability, including freight GPS data analyses [21]. In addition, a hyperparameter optimization was performed to determine the optimum number of clusters, random state (for results repeatability), and the maximum number of iterations of the model.

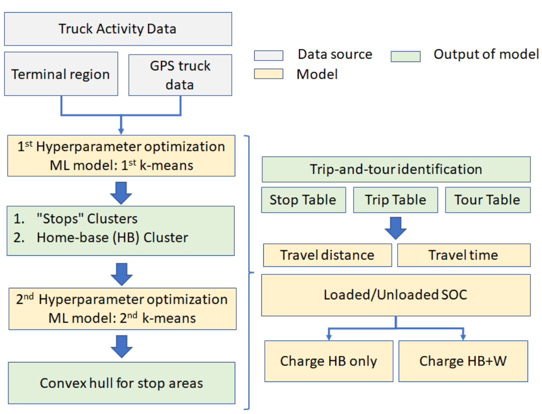



Fig. 1: Proposed methodology. Light orange boxes correspond to models created, grey boxes correspond to data sources, and green boxes correspond to output of the models.

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

To calculate the SOC, we made the following assumptions in our model:

1) Energy performance efficiency for drayage trucks was adapted from [22]. It was assumed a 60% local and 40% freeway operation, resulting in 3.72 kWh/mi for loaded and 1.48 kWh/mi for unloaded trucks;
2) Trucks are unloaded when coming from the home-base and loaded when coming from the port. The other statuses were manually assigned;
3) Battery capacity was adapted from [23] with a usable battery capacity of 300 kWh assuming a 80% battery state of health protection;
4) 100% SOC at the beginning of the first trip; and
5) A 50 kW and 150 kW charger were used, neglecting charging losses.

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

## IV. RESULTS AND DISCUSSION

Figure 2 shows the results of the first k-means clustering using latitude, longitude, and $\Delta$ time in minutes. It is clearly seen that Cluster 0 contains most of the points that represent the truck constantly moving. The aligned vertical clusters with a large $\Delta$ time were assumed to be the home-base. Hyper-parameter optimization was performed giving the optimum number of clusters of 11 for Truck B and 14 for Truck A. The distributions of Cluster 0 (shown in blue color in Figure 2) are presented in Figure 3. As described in Section III, Cluster 0 was removed to isolate the clusters where the truck spent more time stopped. Although 99th percentile of Cluster 0 has a $\Delta$ time of 1.65 minutes, there are still some data points with a larger $\Delta$ time. Consequently, some corrections were applied to correct the shape of the convex hulls (Figure 4) that had some relevant points being removed during this step. Convex hulls computed as a results of the second k-means performed using only GPS latitude and longitude for Truck A are presented in Figure 4. There were some single-point stops usually located near freeways, so a 0.18 miles radius polygon was constructed around each single-point stop. After getting the convex hulls for the stops for both trucks, the trip-and-tour identification

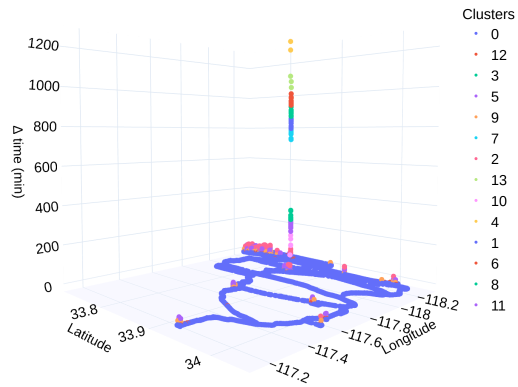



Fig. 2: Results of the first hyperparameter optimization and k-means clustering for Truck A from July to October 2021. The optimum number of clusters was 11 and 14 for Truck B and A respectively.

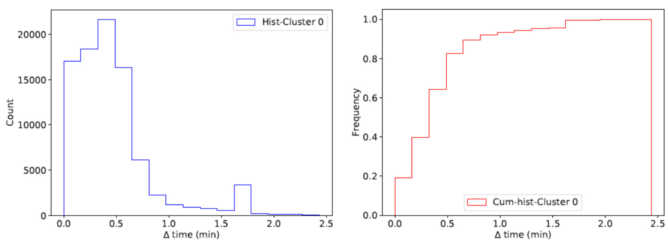



Fig. 3: Histogram (left) and cumulative histogram (right) of Cluster 0 after performing the first k-means for Truck A from July to October 2021. 99th percentile of Cluster 0 has a $\Delta$ time of 1.65 minutes.

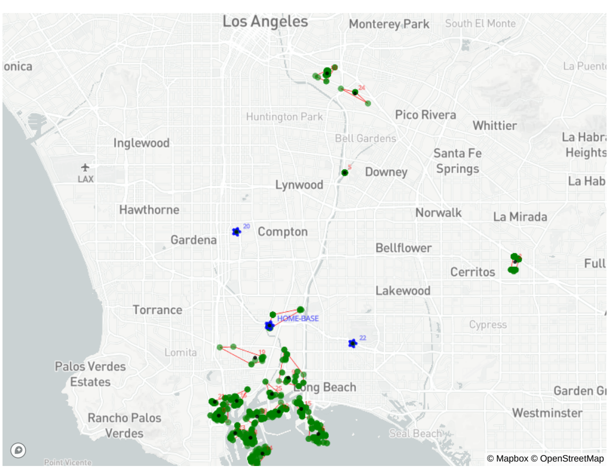



Fig. 4: Convex hulls (red) computed for the 26 clusters (green) from the second k-means model for Truck A from July to October 2021. The home-base and single-point stops are also presented (blue).

was performed over a smaller dataset from August 2-3 2021 for both Trucks A and B. Figure 5 compares the locations that Truck A and B visited during August 2-3, 2021. It is observed that Truck A visited the port, four stops, and also the home-base for a longer period of time. On the contrary, Truck B visited the port, three stops, and its stops at the home-base were shorter. The trip-table for Truck B from August 2-3, 2021

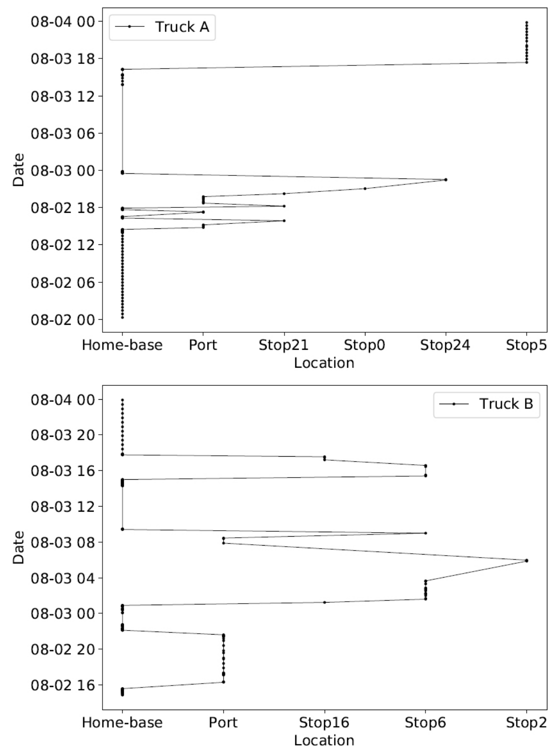


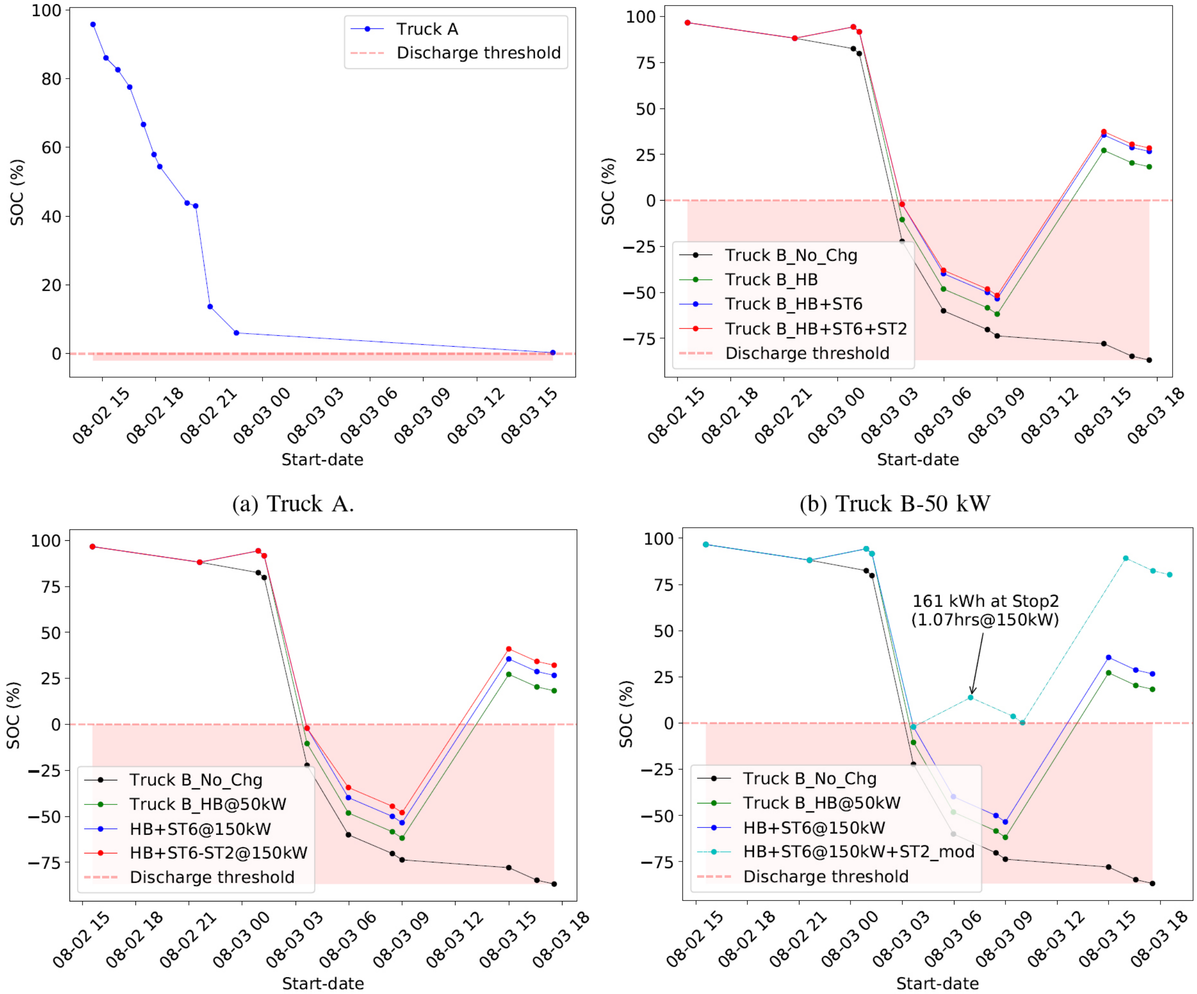

Fig. 5: Locations visited by Trucks A (top) and B (bottom) from August 2-3 2021.

is presented in Table I. This truck had 11 trips, represented by each row in the table, and 3 tours (from home-base to home-base) over a two day period. Cumulative travel distance was 216 miles and cumulative travel time was 5.2 hours for Truck B. On the other hand, cumulative travel distance was 118 miles and cumulative travel time was 3.6 hours for Truck A. Figure 6 shows different modeled SOC scenarios

TABLE I: Trip-table for Truck B from August 2-3 2021.

| **Trip-Table: Truck B** | | | |
|---|---|---|---|
| ***Start Location*** | ***End Location*** | ***Travel distance (mi)*** | ***Travel time (min)*** |
| Home-base | Port | 6.854 | 13.403 |
| Port | Home-base | 6.830 | 13.238 |
| Home-base | Stop16 | 4.572 | 8.535 |
| Stop16 | Stop6 | 5.441 | 12.032 |
| Stop6 | Stop2 | 82.318 | 97.838 |
| Stop2 | Port | 76.494 | 102.145 |
| Port | Stop6 | 8.232 | 18.312 |
| Stop6 | Home-base | 6.946 | 13.747 |
| Home-base | Stop6 | 8.577 | 14.527 |
| Stop6 | Stop16 | 5.507 | 11.697 |
| Stop16 | Home-base | 4.212 | 7.908 |

for Trucks A and B. It is observed that Truck A is able to




(a) Truck A.

(b) Truck B-50 kW

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

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

Fig. 6: SOC scenario for Truck A from August 2-3 2021 (a). SOC scenarios for Truck B from August 2-3 2021 using a 50 kW charger (b). SOC scenarios for Truck B from August 2-3 2021 using a 50 kW charger at home-base and 150 kW charger at Stop6 and Stop2 (c). SOC scenarios for Truck B from August 2-3 2021 using a $50kW$ charger at home-base, 150 kW charger at Stop6, and 150 kW at Stop2 but extending its stay from 0.11 to 1.07 hours adding 161 kWh (d). Shaded red area represents the discharge threshold (HB=home-base, No_Chg=No Charging, ST6=Stop 6, ST2=Stop 2, ST2_mod= Stop 2 modified).

complete all the trips without requiring en-route opportunity charging (Figure 6a). However, Truck B shows a different case. When modeling the scenario of home-base only en-route opportunity charging with a 50 kW power level (Figure 6b), an improvement in the SOC is observed when compared to the no charging scenario. However, its battery will be discharged before completing the fifth trip from Stop6 to Stop2. When modifying the en-route charging scenario at home-base+Stop6, about 100 kWh were added to the battery SOC as the truck spent about 2 hours in this stop (Stop6). Thus, the truck would be able to complete the fifth trip (Stop6 to Stop2) ending with a -2% SOC by using its reserved battery capacity, but its battery will be discharged before completing the next trip from Stop2 to the Port. Moreover, the truck did not spend enough time at Stop2, so even if some en-route opportunity charging is added at this stop (home-base+Stop6+Stop2 scenario), there is no significant improvement in SOC when using a 50 kW charger unless the truck spends more time at this stop. Similarly, SOC scenarios were modeled for Truck B using en-route opportunity charging at a higher power level of 150 kW. For the case of charging at the home-base only (Figure 6c), there is no significant difference in the SOC when using a power level of 50 or 150 kW because the truck spent enough time there to be able to fully recharge its battery. Moreover, there is no significant improvement when increasing the power level at Stop 6 from 50 to 150 kW. The truck did not consume a notable amount of energy from previous trips and it is almost fully charged before starting the fifth trip. So the truck ends with a -2% SOC after the Stop6 to Stop2 trip, regardless of the power level that we have in Stop6 because of the travel distance of the trip. In addition, a small SOC improvement is observed when modeling the en-route opportunity charging scenario using a power level of 150 kW at Stop2. Finally, as shown in Figure 6d, Truck B will be able to complete all of its trips by using a 150 kW power level at Stop2 and by extending its stay at Stop2 from 0.11 to 1.07 hours recharging 161 kWh to its battery.

## V. CONCLUSIONS & FUTURE WORK

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

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