An Intelligently Controlled Charging Model for Battery Electric Trucks in Drayage Operations

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***Abstract*—California has set a goal for all drayage trucks operating in the state to be zero-emitting by 2035. In order to achieve this goal, drayage operators would need to transition 100% of their fleets to zero-emission vehicles such as battery electric trucks (BETs). This article presents an intelligently controlled charging model for BETs that minimizes charging costs while optimizing subsequent tour completion. To develop this model, real-world activity data from a drayage truck fleet operating in Southern California was combined with a two-stage clustering technique to identify trip and tour patterns. The energy consumption for each trip and tour was then simulated for BETs with a battery capacity of 565 kWh using a 150 kW charging power level. Home base charging load profiles were generated using the proposed charging model, subject to constraints of the energy needed to complete the next subsequent tour and Time-of-Use energy cost rates. A sensitivity analysis evaluated three scenarios: a passive scenario with a 5% state-of-charge (SOC) constraint after completing the subsequent tour, an average scenario with a 50% SOC constraint, and an aggressive scenario with an 80% SOC constraint. Results indicated that the 80% SOC constraint scenario achieved the lowest charging cost. However, it also yielded the lowest tour completion rate (51%). In contrast, the 5% SOC constraint scenario registered the highest tour completion rate. These results revealed that 96% of the tours could be successfully completed using the intelligently controlled charging model. The remaining tours were infeasible, indicating that the available time at the home base was inadequate for charging the necessary energy for the next tour. In terms of total costs, the scenario with a 5% SOC constraint resulted in an annual cost of approximately $40,000, whereas the 80% SOC scenario nearly doubled that amount.**

***Index Terms*—Smart charging, battery electric trucks, charging load profile, drayage trucks.**

I. Introduction

The transportation sector accounts for approximately 40% of the total greenhouse gas (GHG) emissions in California, making it the largest source of GHG emissions, according to the 2022 inventory report by the California Air Resources Board (CARB) [1]. In addition to being the largest source of GHG emissions, the transportation sector is also responsible for a significant portion of air pollutants such as oxides of nitrogen (NOx) and particulate matter (PM), which pose health risks such as asthma, heart attacks, and cancer [2], [3]. Medium-duty (MD) and heavy-duty (HD) mobile sources are responsible for 67% of NOx emissions in California, while light-duty (LD) sources account for only 13% of NOx emissions in the state [4].One reason for this difference is that most HD vehicles are diesel-powered, which produce higher NOx emissions per mile than gasoline-powered vehicles. Additionally, HD vehicles travel more miles per year, with an average of 62,229 miles per year, while an average car travels 10,589 miles per year [5]. In recent years, various efforts have been made to reduce emissions from the transportation sector, and one of the latest strategies is transportation electrification. According to the American Council for an Energy-Efficient Economy (ACEEE), California is the leading state in the US for its efforts towards transportation electrification, having set a target for statewide deployment of zero-emission vehicles (ZEVs) while considering the impact of transportation on disadvantaged communities [6].

To address air pollution and climate change, California Governor issued Executive Order N-79-20 in September 2020, which is a crucial step towards achieving carbon neutrality by 2045 [7]. 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.

CARB estimates that electrifying the MD and HD sectors will be crucial to meet California's targets, with a minimum of 157,000 chargers needed to support an estimated 180,000 MD and HD vehicles by 2030. In January 2021, the California Energy Commission (CEC) assessed the electric vehicle (EV) charging infrastructure and identified key actions needed by 2030, including supporting innovative charging solutions and modeling efforts to determine the quantities, locations, and load curves of chargers required to meet statewide travel demand, including for MD and HD vehicles [7]. Currently, EV charging techniques are categorized as uncontrolled or controlled [8]. Uncontrolled charging draws power immediately upon connection,

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typically continuing until the battery is full or halted by the user. Controlled charging includes:

- Indirect: Leverages user behavior for grid load control.
- Intelligent: Data-driven, optimizing available resources within constraints such as energy demand and battery capacity.
- Multistage Hierarchical: Utilizes a priority-based decision tool, blending decision control with genetic algorithms and either fuzzy logic or Artificial Intelligence (AI)-based tools.

The Ports of Los Angeles and Long Beach, collectively known as the San Pedro Bay Ports, are the largest container shipping ports in the US, handling around 40% of the nation's waterborne imported cargo [9]. Consequently, the California South Coast region, where these ports are located, is among the worst in the US that are affected by air pollution related to truck activities, especially in drayage operations. To address this issue, CARB has highlighted the significance of electrification efforts and charging strategies for MD and HD fleets, with a special emphasis on Class 8 drayage trucks [10]. To efficiently project the required charging infrastructure and develop innovative solutions to meet the increasing charging demand from HD BETs, an intelligently controlled charging model was developed and evaluated using real-world activity data of drayage trucks at the Ports of Los Angeles and Long Beach. The main contributions are listed below:

- This intelligently controlled charging model is specifically designed for BETs, which takes into account Time-of-Use (TOU) energy cost rates to optimize subsequent tour completion and minimize charging costs, representing a pioneering approach in BET charging.
- This model's application was demonstrated by generating home base load profiles, analyzing one year worth of real-world activity data from a fleet of 20 drayage trucks operating at the Ports of Los Angeles and Long Beach. The modeled trucks have a battery capacity of 565 kWh and are charged using a 150 kW power level.
- A sensitivity analysis was performed to compare the results of three scenarios–with 5%, 50%, and 80% reserved SOC after completing the subsequent tour.

This article is organized as follows. First, prior research efforts related to HD truck electrification are reviewed in Section II. Then, the dataset and methodology used in our study are described in Section III. Next, the results and discussion of the intelligently controlled charging model are provided in Section IV. Finally, conclusions and future work are presented in Section V.

II. Related Work

In recent years, there have been multiple efforts to understand truck activity, grid impacts, and charging models for drayage fleets, especially as drayage truck fleets are anticipated to become more electrified and connected in the future [11]. Drayage trucks, which transport cargo containers between ports and nearby distribution centers daily, are considered an ideal candidate for electrification due to their predictable activity patterns. Drayage trucks travel a limited distance each day, which is likely to be shorter than the driving range of current BET technologies. They return to home base every night, which allows them to be charged at the home base overnight. Based on an analysis of truck trips, Ambrose [12] reported that less than 1% of drayage trucks completed more than five trips per shift. In a separate study, Tanvir et al. [13] analyzed the activity of drayage trucks in Southern California to estimate the corresponding electric energy consumption and SOC of their batteries. Their results suggest that BETs can serve 85% of the tours if they can be opportunity charged at the home base between consecutive tours. Activity patterns of HD trucks have also been studied. McCormack et al. [14] measured truck movements along specific roadway corridors in Washington State using data from the Commercial Vehicle Information System and Networks (CVISN) electronic truck transponders and Global Positioning System (GPS) data from 30,000 trucks. Results showed that GPS devices provided highly accurate data on both travel routes and individual roadway segments used by trucks. This makes the GPS dataset considerably more robust than the transponder data. Ma et al. [15] analyzed GPS truck data to develop performance measures for truck-based freight network monitoring. Truck travel patterns were identified using an algorithm that differentiated between traffic-based stops and intended stops. This algorithm utilized average stop duration (i.e., dwell time), and the results were manually inspected. The findings presented travel time and speed, roadway location, and stop location information for a fleet of 2,500 trucks in the Puget Sound, Washington region. You et al. [16] developed a comprehensive framework for processing GPS data from clean trucks at California's San Pedro Bay Ports. Data from 545 trucks were filtered and manually checked for truck-accessible locations using Google Earth. Four tour type patterns were analyzed, concluding that the tour characteristics of trucks vary significantly based on fuel type and cargo moves. Similarly, Patel et al. [17] utilized a Random Forest classifier to categorize truck stop locations as either primary or secondary using GPS data. Their proposed machine learning model can identify primary stop locations with an accuracy of 97%. Zhu et al. [18] conducted a systematic study on the impact of charging loads of HD EVs on the electric power grid. They used a methodology that takes into account the location of chargers, load modeling, and grid impact analysis, and compared the results using one model distribution feeder and a realistic California feeder. The study revealed the impact of charging stations on the grid and suggested that different mitigation plans, such as the use of smart chargers, can provide reactive power support. Fjaer et al. [19] modeled the aggregated load profiles of high-energy charging stations utilized by HD EVs in Eastern Norway, considering peak loads of 4, 9, and 13 MW. The findings showed that the peak loads associated with HD EVs caused the electrical distribution substation to surpass its rated capacity and thermal limit. To address this issue, the authors suggested reducing the peak load by extending the drivers' break time by 15 minutes, which would enable the operation of the electrical distribution substation to remain below the rated capacity. This recommendation aimed to ensure that the substation operates within its limit and provides a stable power supply.

Borlaug et al. [20] investigated the impacts of depot charging by developing synthetic load profiles for short-haul HD EVs, which were applied to 36 distribution substations. The results showed that 78-86% of the substations were capable of supplying HD charging without upgrades. In [21], a simulation was conducted to assess the impact of HD charging on a distribution system in Texas. The findings indicated that the transmission grid experienced a significant impact when charging only 11% of the simulated HD EVs, highlighting the need for infrastructure upgrades and further studies of smart charging models. Similarly, Tong et al. [22] analyzed the charging load profiles of HD EVs, which demonstrated that the daily charging peak is highly influenced by long-haul truck operations, as well as the peaks in solar power generation in California. Smart charging for HD EVs, explored in [23], used data from 259 U.S. HD EVs to gauge peak demand impacts. Modeling two battery capacities and charging levels, the findings showed that smart charging could reduce peak demand by 1,095 kW, potentially saving up to $10,000 monthly.

The review of these prior research efforts suggests significant gaps in the existing literature concerning pattern recognition of drayage truck operation, stop locations, and energy consumption. Moreover, while the estimation of grid impacts from HD truck charging has been explored, it has not been specifically examined for drayage operations. Lastly, the development of intelligent charging models tailored for HD trucks is almost non-existent.

While there are various factors that affect the performance of BETs, including temperature conditions, battery degradation, and battery cell imbalance, electric trucks are greatly influenced by technological advancements. Given the rapid progress in battery technology, the battery feasibility of HD BETs is changing rapidly [24]. Consequently, the literature on battery degradation in BETs is limited [25], [26]. Given these gaps and existing limitations, an intelligently controlled charging model is proposed, aiming to maximize tour completion while also minimizing charging costs. This model has been calibrated using a one year worth of real-world activity data from a fleet of 20 drayage trucks operating at the San Pedro Bay Ports in Southern California.

III. Methodology

Truck activity data were analyzed for 20 vehicles belonging to the same fleet operating at the San Pedro Bay Ports terminal regions in Long Beach and Los Angeles from July 2021 to August 2022. The available data for each truck included ID (TruckId), latitude, longitude, and GPS date/time. Furthermore, data for each truck at different terminal regions were also available, including the terminal name, tract name, enter date/time to the terminal, and exit date/time from the terminal. The frequency of the activity data was not uniform as the vehicle position and GPS date/time were recorded only when the trucks moved along the road. Hence, no data were recorded if there was no movement. This fleet typically covers routes in Los Angeles, San Bernardino, and Riverside counties, as illustrated in Fig. 1.

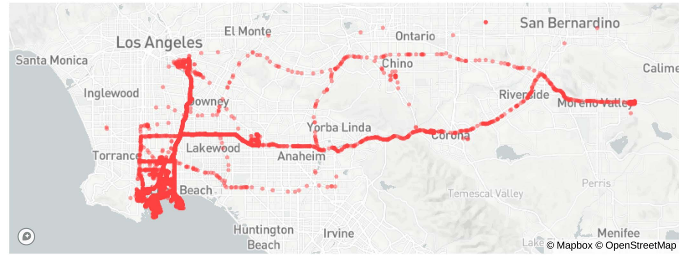

Fig. 1. Typical routes for the 20 drayage trucks included in this study.

A. Identifying Trips and Tours

The raw GPS data were first pre-processed and filtered by terminal region and TruckId. However, the data were not labeled in terms of stops. To solve this issue, a two-staged unsupervised machine learning (ML) technique called k-Means clustering was adapted from [27] and implemented in Python to identify the home base and loading/unloading stops for the trucks. The k-Means algorithm was used to cluster the data by separating them into groups while minimizing the within-cluster sum-of-squares [28]. This algorithm was selected because of its scalability and widespread use across various applications. Additionally, the GPS date/time differential was calculated to determine the time gap between consecutive timestamps. A cluster of data points on the map with a large time gap between timestamps suggests a potential home base or warehouse where trucks stop to load/unload cargo. In contrast, a cluster of data points on the map with a small time gap between timestamps implies that the truck is continuously moving, and is unlikely to represent a meaningful stop. Hyperparameter optimization was also conducted to determine the optimal number of clusters for the initial k-Means by calculating the average time differential and the 99th percentile in minutes for the cluster designated for removal.

Fig. 2 summarizes this methodology. After identifying potential truck stops and the home base using the first k-Means, a second k-Means model was implemented. The main aim was to obtain the convex hulls for each cluster to identify possible truck stops. Therefore, based on the original activity of the truck, every time the truck enters a convex hull and spends a significant amount of time there, the potential stop will be labeled as a significant stop. Finally, a hyperparameter optimization was also performed for the second k-Means model to determine the optimum number of clusters, maximum number of iterations of the model, and random state for result repeatability. To determine the optimal number of clusters for the second k-Means model, the Elbow method (improvement in distortion declines) was used, which involves calculating the inertia. Inertia is a measure of how well a dataset is clustered by k-Means. It is calculated by measuring the distance between each data point and its centroid, squaring this distance, and then summing these squares across one cluster. A good model is characterized by low inertia and a minimal number of clusters [29], [30].

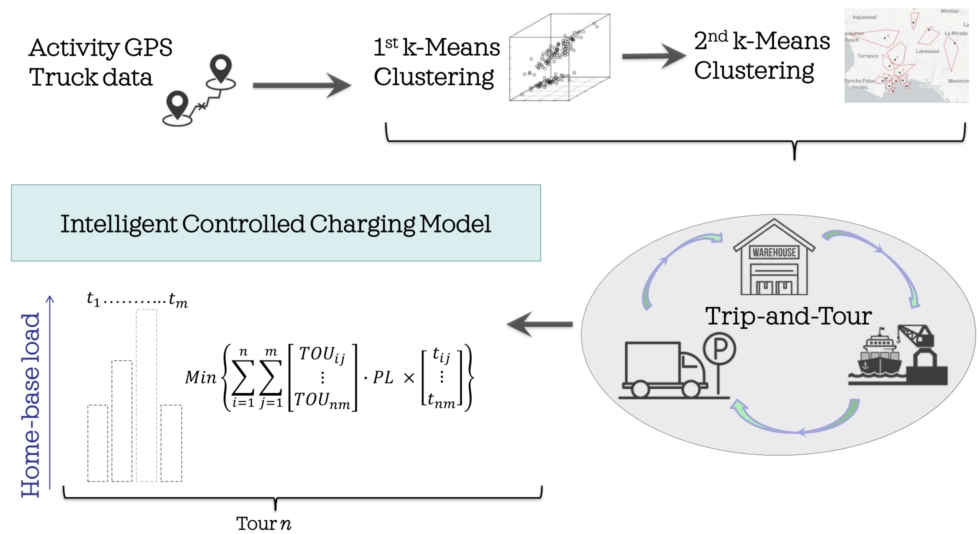

Fig. 2. Proposed methodology. Intelligently controlled charging model is based on one year worth of real-world activity data from a fleet of 20 drayage trucks operating at the San Pedro Bay Ports.

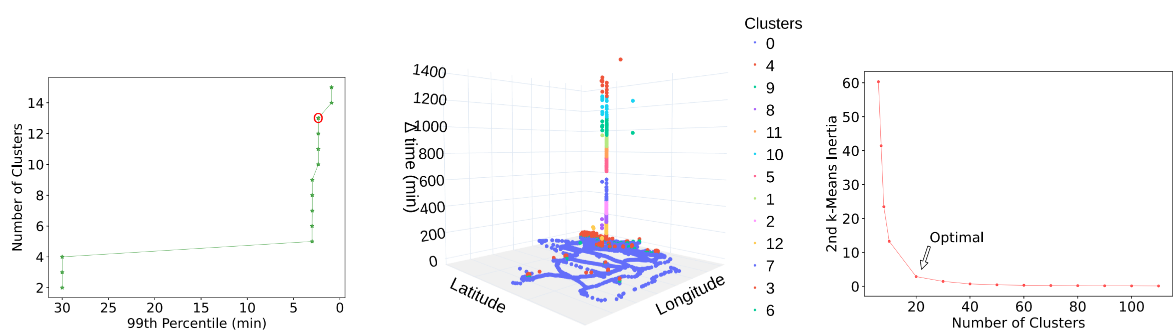

Fig. 3. Results of the first k-Means hyperparameter optimization (left), the time differential plot (middle), and the second k-Means hyperparameter optimization (right) for a fleet of 20 trucks using data from July 2021 to August 2022. The optimal numbers of clusters for the first and second k-Means models were 13 and 20, respectively.

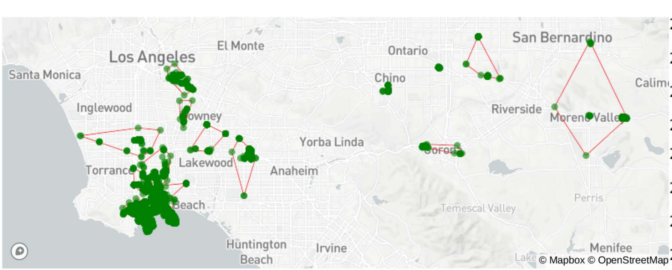

Fig. 4. Results of applying the second k-means model to a fleet of 20 trucks using data from July 2021 to August 2022. The 20 resulting clusters are represented by green dots and enclosed in red convex hulls. Additionally, a manual convex hull was assigned to the data to indicate the home base.

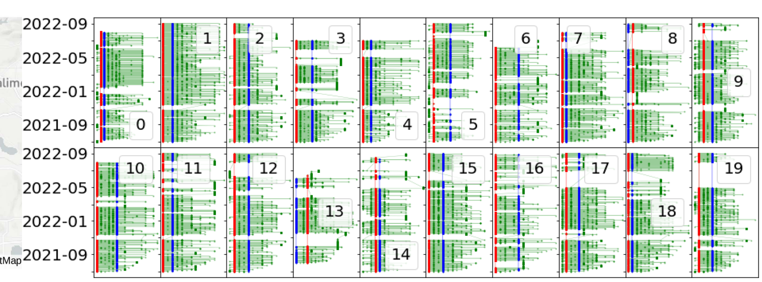

Fig. 5. Locations visited by Trucks 0 to 19 between July 2021 and August 2022. The red dots represent a stop at the home base, while the blue dots represent a stop at the port.

Trips and tours were generated from the identified stops and home base. A truck trip serves a specific purpose, such as picking up a container from the port or delivering it to a warehouse. A truck tour consists of a sequence of truck trips. In this study, a truck tour is defined as starting and ending at the home base location. Tour travel distances for each truck were determined using a maps, routing, and navigation Application Programming Interface (API) in Python. It is assumed that trucks were unloaded when traveling from the home base and loaded when traveling from the ports. The loaded/unloaded status was maintained between the end of the previous tour and the beginning of the next tour. Within a tour, the status alternates between loaded and unloaded for each trip. To calculate energy consumption, energy efficiency values from [27], [31] were utilized, with loaded and

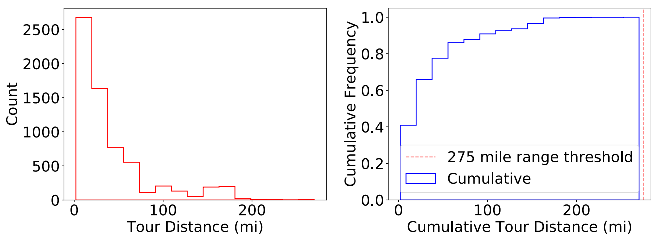

Fig. 6. Tour distance distribution (left) and normalized cumulative tour distance (right) for a fleet of 20 trucks operating at the San Pedro Bay ports between July 2021 and August 2022. The figure also includes a threshold of 275 miles, as it has been suggested in [32] that this is the expected range for a 565 kWh battery electric truck.

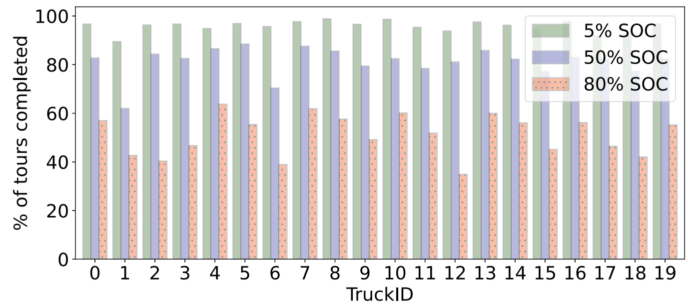

Fig. 8. Percentage of tours completed per truck under the three modeled scenarios for a fleet of 20 trucks operating at the San Pedro Bay ports between July 2021 and August 2022.

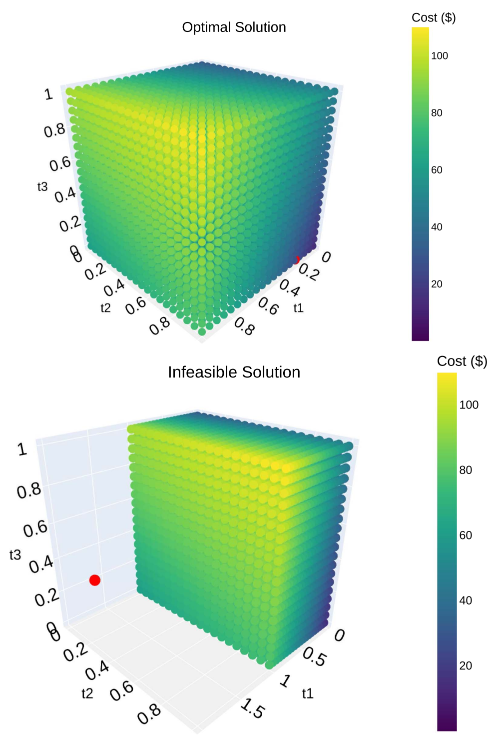

Fig. 7. Optimal (top) vs. Infeasible (bottom) solutions from the optimization model for a truck that spends 3 hours at the home-base. Each axis (t_1,t_2,t_3) represents the hourly bin that needs to be optimized. Colormap represents the charging cost in \$. Red dot represents the solution given by the optimization model.

unloaded trucks consuming 3.72 kWh/mi and 1.48 kWh/mi, respectively.

B. Intelligently Controlled Charging Model

The intelligently controlled charging model optimizes charging resources such as energy cost and efficiency based on various constraints, including grid energy demand, battery capacity, network structure, and transformer efficiency, using data-driven approaches [8]. After processing trip and tour data for each truck, as well as their respective timestamps for entering and exiting the home base location, an intelligent controlled charging model for our fleet scenario is proposed.

1) *Setup and Assumptions:* The following assumptions were made for the model:

- Each truck has a nominal battery capacity of 565 kWh, with 80% usable capacity for state-of-health protection purposes [32];
- The truck battery is 100% charged at the beginning of the first tour;
- Charging is modeled using a 150 kW charger, and assuming a 85% charging efficiency adapted from [33];
- When the time at the home base exceeds 24 hours, the charging session will occur during the first 24 hours;
- The electrical load profile modeled at the home base only considers the charging of BETs.
- The effects of temperature conditions are neglected;
- Battery degradation and battery cell imbalance during charging are neglected;

2) *Objective Function:* Goal is to minimize the total charging cost and maximize subsequent tour completion by optimizing the charging time. Thus, for the objective function described in (1), the charging time t in hours for each hour j and tour i is given by:

$$\text{Minimize} \sum_{i=1}^{n}\sum_{j=1}^{m} \begin{bmatrix} TOU_{ij} \\ \vdots \\ TOU_{nm} \end{bmatrix} \cdot \eta_c PL \times \begin{bmatrix} t_{ij} \\ \vdots \\ t_{nm} \end{bmatrix}$$

$$\text{With: } t_{ij} \in \mathbb{R}^n \tag{1}$$

3) **Constraints:**

- Setting lower bounds:

$$\text{C1: } t_{ij}, \ldots, t_{nm} \geq 0 \tag{2}$$

- Setting upper bounds:

$$\text{C2: } [t_{ij}, \ldots, t_{nm}] \leq [K_{ij}, \ldots, K_{nm}] \tag{3}$$

- The total charging time should not exceed the maximum battery capacity:

$$\text{C3: } t_{ij} + \ldots + t_{nm} \leq T_i \tag{4}$$

- After charging, the SOC minus the energy for the next tour should meet the SOC constraint:

$$\text{C4: } \frac{(BR_i + (C3) \times \eta_c PL) - E_{i+1}}{0.8 \times BC} \geq SOC_c \tag{5}$$

Where:

TABLE I
2019-2023 TOU-EV-9 RATES SCE [34], [35]

Energy Charge	Description	$\$/kWh$
Summer on-peak	Jun 1 - Sep 30 weekdays 4:00pm-9:00pm	0.412
Summer mid-peak	Jun 1 - Sep 30 weekends-holidays 4:00pm-9:00pm	0.218
Summer off-peak	Jun 1 - Sep 30 any other time	0.102
Winter mid-peak	Oct 1 - May 31 4:00pm-9:00pm	0.250
Winter off-peak	Oct 1 - May 31 00:00am-8:00am and 9pm-00am	0.107
Winter super-off-peak	Oct 1 - May 31 8:00am-4:00pm	0.067

$t =$ charging time in hours;
$i=$ number of the tour;
$n =$ total number of tours;
$j =$ hourly bin to charge at each tour;
$m =$ total number of hours (bins) available at the home base to charge;
$\eta_c =$ charging efficiency equals to 0.85;
$PL =$ charging power level at the home base equals to 150 kW;
$BC =$ truck battery capacity equals to 565 kWh;
$K_{ij} =$ time remaining in hours to charge within the hourly bin (≤ 1);
$T_i =$ time needed in tour i to have a fully charged battery in hours;
$BR_i =$ battery remaining after tour i;
$E_{i+1} =$ kWh needed to cover subsequent tour $(i+1)$;
$SOC_c =$ Model constraints of 5%, 50%, and 80% represent the reserved SOC after completing the subsequent tour $(i+1)$; and
$TOU_{ij} =$ TOU-EV-9 rate is applied for each tour i and hour j at the home base, which is located in a zipcode covered by Southern California Edison (SCE). The specific TOU rates are summarized in Table I.

4) *Optimization Technique:* The proposed algorithm shown in Algorithm 1 defines an optimization problem using the Python PuLP library [36]. PuLP is a free, open-source software written in Python. It is primarily used to describe optimization problems as mathematical models. Once defined, PuLP can call various external linear programming solvers, such as CBC, GLPK, CPLEX, Gurobi, etc., to solve the model. The model uses the CBC (Coin-or branch and cut) solver. This is an open-source solver that comes bundled with PuLP. For many standard problems, particularly smaller ones, CBC is quite effective. Other solvers like Sequential Least Squares Quadratic Programming (SLSQP) and Nelder-Mead are available in the Scipy.optimize Python package [37]. These two solvers are particularly effective for non-linear optimization problems. While SLSQP is straightforward to use, Nelder-Mead does not enforce constraint handling.
The optimization problem is set up as a minimization problem with the objective function defined as the dot product of the TOU rates, power levels, and t_{ij} variables, which represent the amount of time spent charging in hourly bins. The variables are created as a dictionary using the LpVariable method, and the lowBound parameter is set to 0 to ensure non-negativity. The algorithm then sets up several constraints related to the variables, including upper bounds on the charging time and a constraint on the reserved SOC of the battery after the next subsequent tour. Finally, the optimization problem is solved using the solve method of the LpProblem class.

5) *Results:* The outcome provides the optimal charging duration for each hourly bin to construct the home-base charging load profile.

Algorithm 1: Intelligent Controlled Charging Algorithm.

$Lp_{prob} \leftarrow p.LpProblem('Problem', p.LpMinimize)$
$t_{array} \leftarrow [\ ]$
for $i \leftarrow 1$ to n **do**
  for $j \leftarrow 1$ to m **do**
    $t[ij] \leftarrow p.LpVariable("t''_{ij}, lowBound = 0)$
    $Lp_{prob} \leftarrow [TOUij] \cdot \eta_c PL \times [t_{ij}]$
    $Lp_{prob} \leftarrow tij \leq kij$
  end for
end for
return t_{array}
for $i \leftarrow 1$ to n **do**
  $Lp_{prob} \leftarrow p.lpSum(t_{array}) \leq Ti$
  $Lp_{prob} \leftarrow \frac{(BR_i + (p.lpSum(t_{array}) * \eta_c PL) - E_{i+1})}{0.8 \times BC} \geq SOC_c$
  $status \leftarrow Lp_{prob}.solve()$
end for
return t_{array}

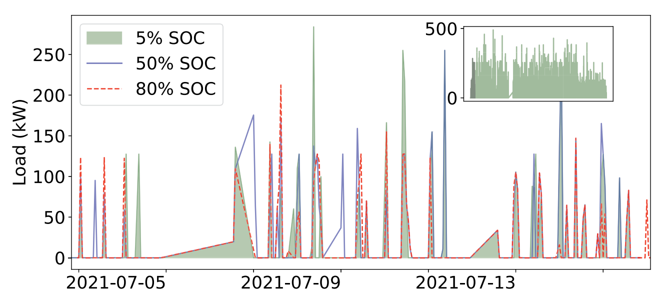

Fig. 9. Hourly home base load profile in kW generated for the month of July 2021 for a fleet of 20 trucks using the intelligent controlled charging model with three SOC constraints. The zoom-out figure presents the hourly profile from July 2021 to August 2022 for the 5% SOC constrained scenario.

IV. RESULTS AND DISCUSSION

The results of the sensitivity analysis for determining the optimal number of clusters are shown in Fig. 3. For the initial k-Means, the optimal number of clusters was determined by calculating both the average time and the 99th percentile in minutes for cluster 0 situated at the bottom (as seen in Fig. 3 middle). This cluster represents the truck constantly moving and

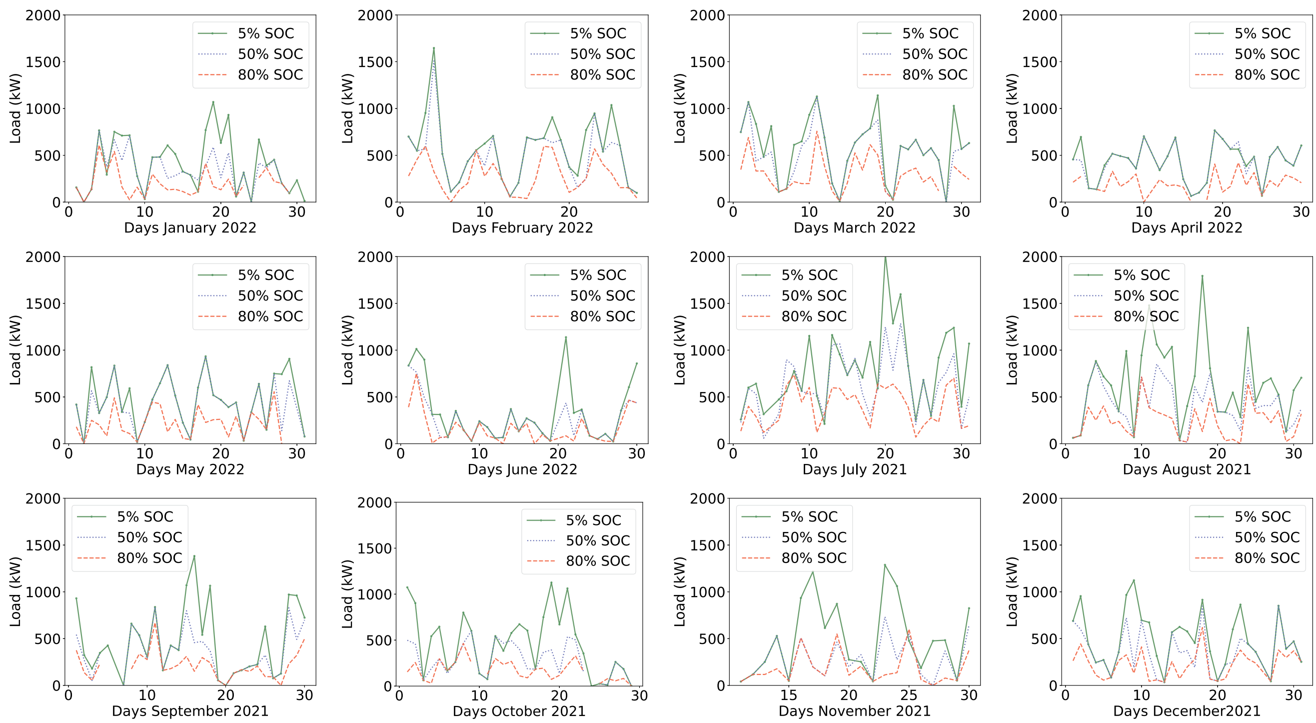

Fig. 10. Aggregated daily load profile per month at the home base in kW for a fleet of 20 trucks using data from July 1, 2021 to June 30, 2022, showing a one-year seasonality.

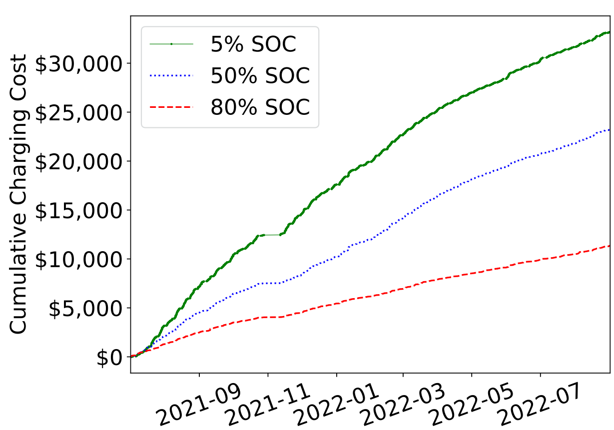

Fig. 11. Cumulative energy charging cost using the TOU-EV-9 rates for the three SOC constrained scenarios from July 2021 to August 2022.

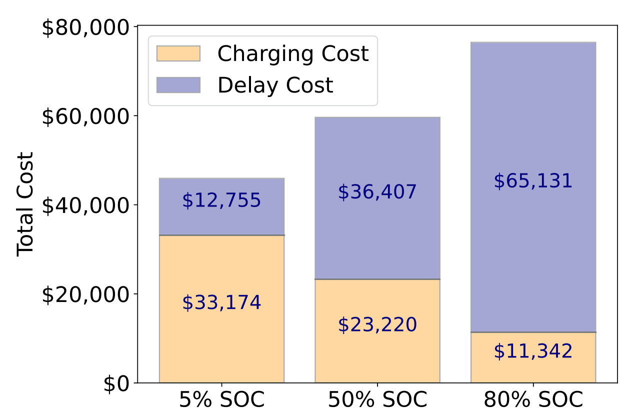

Fig. 12. Charging vs. Delay costs for the three SOC constrained scenarios from July 2021 to August 2022.

does not indicate potential stops for the truck. This cluster was subsequently excluded from the analysis. Therefore, with 13 modeled clusters, the cluster designated for removal has a mean of 0.7 minutes, and 99% of the points halted for 2.3 minutes or fewer (Fig. 3 left). Increasing the total number of clusters to 14 causes 99% of the points in the cluster designated for removal to stop for 0.9 minutes or less, a duration considerably shorter than the 3-minute threshold found in the literature [14], [15]. The result of the Elbow method to determine the optimal number of clusters for the second k-Means model is shown in Fig. 3-right.

Convex hulls computed as a results of the second k-means performed using only GPS latitude and longitude are presented in Fig. 4.

After obtaining the convex hulls for the stops of both trucks, trip-and-tour identification was conducted. Fig. 5 presents a comparison of the locations visited by Trucks 0 to 19 from July 2021 to August 2022, emphasizing the variability in travel patterns across the fleet. Some trucks, such as Truck 1, display more active travel patterns, while others, like Truck 13, show notably less activity. Moreover, it's evident that certain trucks make more intermediate stops between the home base (red dots) and the port (blue dots). This variability is further highlighted

TABLE II
NUMBER OF TOURS AND TRIPS PER TRUCK FOR A FLEET OF 20 TRUCKS USING DATA FROM JULY 2021 TO AUGUST 2022

TruckId	# of Tours	# of trip
0	369	1273
1	411	1449
2	395	1281
3	316	1148
4	308	991
5	245	816
6	224	756
7	395	1395
8	299	970
9	418	1441
10	389	1333
11	309	1043
12	309	1009
13	204	793
14	335	1072
15	389	1469
16	237	754
17	357	1356
18	303	1121
19	336	1192

TABLE III
TOTAL NUMBER OF TOURS COMPLETED PER CONSTRAINED SCENARIOS

SOC Constraint	N° Tours Optimal Sol.	N° Tours Infeasible Sol.	% Tours Completed
5%	3563	153	95.9%
50%	3020	696	81.3%
80%	1806	1910	51.4%

in Table II, which lists the number of trips and tours per truck over one year.

Fig. 6 displays the tour travel distance and cumulative distributions for a fleet of 20 trucks operating at the San Pedro Bay ports from July 2021 to August 2022. It is worth noting that all tours in the fleet have a travel distance less than the 275-mile range for a truck with a 565 kWh battery capacity [32]. Achieving a 275-mile range would require an assumed energy efficiency of 2 kWh per mile, but it is important to consider that drayage trucks consume varying amounts of kWh per mile depending on factors such as cargo load and road type (freeway or local) [27], [31].

A. Tour Completion Analysis

One of the primary constraints in the intelligently controlled charging model is the completion of subsequent tours. Table III summarizes the percentage of tours completed under the three SOC constrained scenarios. It becomes evident that as the remaining SOC constraint becomes more aggressive, the percentage of completed tours decreases. This is due to the model lacking optimal solutions. The table also indicates the number of tours with optimal and infeasible solutions. As shown in Fig. 7, for a truck that spends 3 hours at the home-base, each axis (t_1, t_2, t_3) represents the hourly bin to be optimized. A tour with an infeasible solution indicates that the available charging time does not satisfy the constraints in (1), preventing the model from completing the next tour, as highlighted by the red dot being outside the cube. Consequently, a scenario with 5% reserved SOC after completing the subsequent tour will result in 96% of tours being completed across the entire fleet. Results from Tanvir et al. [13] suggest that BETs can complete 85% of the tours if they can be opportunity charged at the home base between consecutive tours. Thus, the intelligently controlled charging model can increase the tour completion rate from 85% to 96%. Furthermore, when juxtaposing the results with the normalized cumulative tour distance for this fleet (Fig. 6), it implies that all tours should be completed. However, there remain about 153 tours (4%) that will not be completed in one year.

The percentage of tours completed by each truck under the three modeled scenarios is presented in Fig. 8. It is evident that certain trucks completed more tours than others. For example, while TruckId 11 and 12 both embarked on the same number of tours (as detailed in Table II), they differed in the number of trips made, with 1043 and 1009 trips, respectively. This variation in trips leads to a distinct energy consumption pattern, influenced by the route taken by the truck and whether it is carrying cargo or not.

B. Home Base Load Analysis

Fig. 9 displays the hourly home base load profile in kW generated by the intelligent controlled charging model under the three remaining SOC constraints. This zoomed-out figure highlights the 5% SOC constraint.

The daily aggregated load profile per month in kW, under the three different scenarios considered, is presented in Fig. 10. A seasonality pattern within each month is evident. Patterns corresponding to weekdays are noticeable every approximately five days, representing truck charging during the weekdays and minimal charging over the weekends. Furthermore, a load seasonality in the energy charged can be observed during the Summer months of July and August 2021. This seasonality might also be linked to the type of product the drayage truck transports and its import patterns to the country during specific months of the year. Comparing the three constrained SOC scenarios, the variability introduced by the available charging time at the home base, and subsequently, the number of feasible solutions is evident. This variability is highlighted by the vertical gap in kW between the 5%, 50%, and 80% cases.

C. Cost Analysis

Fig. 11 presents a comparison of the cumulative charging costs from July 2021 to August 2022 for the three SOC constrained scenarios using the TOU-EV-9 rates detailed in Table I. The total cumulative charging cost for one year under the 5% SOC constraint amounts to approximately \$33,000, as outlined in Table IV. However, when contrasted with the 80% SOC scenario, a decrease of 34% in charging cost (from \$33,174 to \$11,341) is observed. Yet, this decrease does not correspond to an equivalent 44% reduction in the number of tours completed. This discrepancy arises from the optimal solutions at each tour, with the number of infeasible solutions not factored into the charging cost.

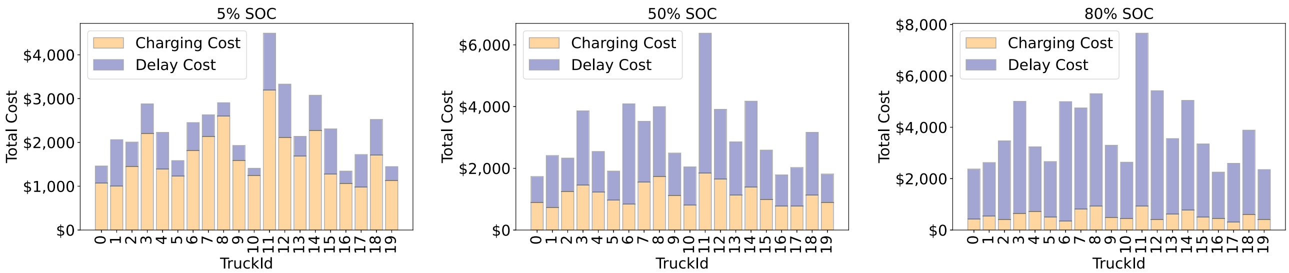

Fig. 13. Charging vs. Delay costs for the three SOC constrained scenarios from July 2021 to August 2022 per TruckId.

TABLE IV
MONTHLY ENERGY CHARGING COST FROM JULY 2021 TO AUGUST 2022 CONSIDERING THE THREE SOC CONSTRAINED SCENARIOS

Year-Month	5% SOC	50% SOC	80% SOC
2021-07	$3,169.2	$2,137.9	$1,294.8
2021-08	$4,018.3	$2,376.9	$1,187.5
2021-09	$3,087.8	$1,896.5	$1,016.8
2021-10	$2,164.1	$1,099.1	$540.7
2021-11	$2,158.7	$868.6	$490.1
2021-12	$3,001.9	$1,870.4	$919.2
2022-01	$2,350.1	$1,757.1	$703.5
2022-02	$2,728.1	$2,143.5	$778.6
2022-03	$2,569.1	$2,326.9	$978.1
2022-04	$1,760.7	$1,659.7	$621.1
2022-05	$1,432.9	$1,270.5	$607.0
2022-06	$1,875.9	$1,336.5	$815.2
2022-07	$1,333.0	$1,056.5	$537.4
2022-08	$1,524.5	$1,419.5	$851.9
TOTAL	**$33,174.3**	**$23,219.7**	**$11,341.9**

For the infeasible solutions, a delay cost of $26.7 per hour from [38] was used to compare optimal vs. infeasible tour solutions, with each tour being analyzed independently. Total charging vs. delay costs are presented in Fig. 12. This clearly indicates that the scenario with 80% SOC has a significant total cost when delay is considered. Finally, the 5% SOC constraint resulted in a total charging and delay cost of about $40,000 per year, whereas the 80% SOC led to almost double that amount.

The total cost per truckId is presented in Fig. 13. Among them, TruckId 11 stands out with notably more variability than the others. This graph serves as a valuable tool for pinpointing the trucks and routes that might benefit from earlier re-routing to diminish delay costs.

V. CONCLUSION & FUTURE WORK

California has set a goal to achieve carbon neutrality by 2045, with a specific target to make all drayage trucks operating in the state be zero-emission vehicles by 2035. Achieving this target requires accurate modeling of the quantities, locations, and load profiles of chargers needed to meet statewide electrification goals. However, there are significant gaps in the current literature regarding pattern recognition of drayage truck operations, stop locations, and energy consumption. Furthermore, the development of intelligent charging models specifically for HD trucks is notably lacking.

Given these gaps, an intelligently controlled charging model has been proposed for BETs. This model takes into account TOU energy cost rates to optimize the completion of subsequent tours and minimize charging costs. It is based on a one-year worth of real-world activity data from a fleet of 20 drayage trucks operating at the San Pedro Bay Ports. The application of this model is demonstrated by generating home base load profiles, taking into account the energy needed to complete the next subsequent tour and the TOU energy cost rates. The performance of the model was assessed under three different scenarios with varying SOC constraints: 5%, 50%, and 80%.

Results showed that when reserving a 5% SOC after the completion of the next subsequent tour, 96% of tours were completed for the entire fleet. This outcome highlights the potential of strategic charging, especially when compared to other findings in the literature, such as those by Tanvir et al. [13]. Furthermore, the 80% SOC constraint proved to yield the lowest charging cost. However, this cost-saving is attributed to the number of infeasible solutions. The cumulative charging cost over a year under the 5% SOC constraint totals around $33,000. In contrast, the 80% SOC scenario registered a 34% reduction in charging costs, dropping from $33,174 to $11,341. In summary, the 5% SOC constraint led to an aggregate charging and delay cost of approximately $40,000 annually, while the 80% SOC nearly doubled that figure.

From the findings presented in this article, it is evident that a significant portion of the tours remains infeasible under current BET technologies, particularly with more aggressive SOC constraints. Addressing these infeasible tours could involve deploying BETs with extended range, introducing faster charging mechanisms, and re-routing BETs to consider their driving range alongside the necessary charging durations for subsequent tour completions.

Future work includes addressing existing gaps and create a model for a more accurate estimation of trip-and-tour energy consumption. The introduction of a re-routing model will further ensure tour completion while optimizing charging costs. The proposed model lays the foundation for intelligent charging solutions tailored for BETs and aligns with California's aspirations for zero-emission drayage trucks. As the model undergoes further refinement, it will incorporate more fleet scenarios. Additionally, analyses will expand to consider factors such as temperature conditions, battery degradation, and battery cell imbalance to provide a more holistic understanding.

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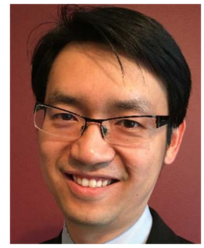

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